IEEE TRANSACTIONS ON CONTROL OF NETWORK SYSTEMS, VOL. 5, NO. 4, DECEMBER 2018

Scheduling of EV Battery Swapping—Part I: Centralized Solution

Pengcheng You, *Student Member, IEEE*, Steven H. Low, *Fellow, IEEE*, Wayes Tushar, *Member, IEEE*, Guangchao Geng, *Member, IEEE*, Chau Yuen, *Senior Member, IEEE*, Zaiyue Yang, *Member, IEEE*, and Youxian Sun

***Abstract*—We formulate an optimal scheduling problem for battery swapping that assigns to each electric vehicle (EV) a best battery station to swap its depleted battery based on its current location and state of charge. The schedule aims to minimize a weighted sum of EVs' travel distance and electricity generation cost over both station assignments and power flow variables, subject to EV range constraints, grid operational constraints, and ac power flow equations. To deal with the nonconvexity of power flow equations and the binary nature of station assignments, we propose a solution based on second-order cone programming (SOCP) relaxation of optimal power flow and generalized Benders decomposition. When the SOCP relaxation is exact, this approach computes a global optimum. We evaluate the performance of the proposed algorithm through simulations. The algorithm requires global information and is suitable for cases where the distribution grid, battery stations, and EVs are managed centrally by the same operator. In Part II of this paper, we develop distributed solutions for cases where they are operated by different organizations that do not share private information.**

***Index Terms*—Battery swapping, convex relaxation, *DistFlow* equations, electric vehicle (EV), generalized Benders decomposition.**

Manuscript received June 25, 2017; revised September 21, 2017; accepted October 26, 2017. Date of publication November 13, 2017; date of current version December 14, 2018. This work was supported in part by the Zhejiang Provincial Natural Science Foundation of China under Grant LR16F030002; in part by NSF under Grant CCF 1637598, Grant ECCS 1619352, and Grant CNS 1545096; in part by the ARPA-E under Grant DE-AR0000699 and the GRID DATA program; in part by the DTRA under Grant HDTRA 1-15-1-0003; in part by the Advance Queensland Research Fellowship AQRF11016-17RD2, which is jointly sponsored by the State of Queensland through the Department of Science, Information Technology and Innovation, the University of Queensland and Redback Technologies; in part by the NSFC under Grant 61750110529; and in part by the SUTD-MIT International Design Center. Recommended by Associate Editor L. Schenato. *(Corresponding author: Zaiyue Yang.)*

P. You, G. Geng, and Y. Sun are with the State Key Laboratory of Industrial Control Technology, Zhejiang University, Hangzhou 310027, China (e-mail: pcyou@zju.edu.cn; ggc@zju.edu.cn; yxsun@iipc.zju.edu.cn).

S. H. Low is with the Engineering and Applied Science Division, California Institute of Technology, Pasadena, CA 91125 USA (e-mail: slow@caltech.edu).

W. Tushar is with the School of Information Technology and Electrical Engineering, The University of Queensland, Brisbane, QLD 4072, Australia (e-mail: wayes.tushar.t@ieee.org).

C. Yuen is with Singapore University of Technology and Design, Singapore 487372 (e-mail: yuenchau@sutd.edu.sg).

Z. Yang is with the Department of Mechanical and Energy Engineering, Southern University of Science and Technology, Shenzhen 518055, China, and also with the State Key Laboratory of Industrial Control Technology, Zhejiang University, Hangzhou 310027, China (e-mail: yangzy3@zju.edu.cn).

Digital Object Identifier 10.1109/TCNS.2017.2773025

I. Introduction

A. Motivation

We ARE at the cusp of a historic transformation of our energy system into a more sustainable form in the coming decades. Electrification of our transportation system will be an important component because vehicles today consume more than a quarter of energy in the USA and emit more than a quarter of energy-related carbon dioxide [1]. Electrification will not only greatly reduce greenhouse gas emission, but also have a big impact on the future grid because electric vehicles (EVs) are large but flexible loads [2]. It is widely believed that uncontrolled EV charging may stress distribution grids and cause voltage instability, but well controlled charging can help stabilize grids and integrate renewables. As we will see below, there is a large literature on various aspects of EV charging.

We study a different problem here, motivated by a battery swapping business model currently being pursued in China, especially for electric buses and taxis [3]. The State Grid (one of the two national utility companies) of China is experimenting with this new business model where it operates not only the distribution grid, but also stations[1] and a taxi service around a city, e.g., Hangzhou. When the state of charge of a State Grid taxi is low, it goes to one of State Grid operated stations to exchange its depleted battery for a fully-charged one. While battery swapping takes only a few minutes, it is not uncommon for taxis to arrive at a station, only to find that it runs out of fully charged batteries and there is a queue of taxis waiting to swap their batteries. The occasional multihour waits are a serious impediment to the battery swapping business model.

This business model reduces range anxiety of EV drivers by eliminating the impact of lengthy battery charging processes on them. It is predicated however on having sufficient fully charged batteries at stations so that drivers rarely have to wait long for battery swapping. In fact, it is often the case that some stations that EVs gather around run short of fully charged batteries, whereas others accrue more and more. Obviously it is

[1] Throughout this paper, stations refers to battery swapping service stations.

impractical to stock enough batteries at every station to serve the worst case EV arrival patterns. In this paper, we propose an approach to coordinate battery swapping such that EVs can make the most efficient use of currently available batteries in the system. Meanwhile, scheduling of battery swapping also redistributes charging loads spatially, which is significant potential for load management and provides an opportunity to jointly optimize the operation of a distribution network.

To this end, we formulate in Section II of this paper an optimal scheduling problem for battery swapping that assigns to each EV a best station to swap its depleted battery based on its current location and state of charge. The station assignments not only determine EVs' travel distance, but also impact significantly the power flows on a distribution network because batteries are large loads. The schedule aims to minimize a weighted sum of EVs' travel distance and electricity generation cost over both station assignments and power flow variables, subject to EV range constraints, grid operational constraints, and ac power flow equations.

This joint battery swapping and optimal power flow (OPF) problem is nonconvex and computationally difficult for two reasons. First, ac power flow equations are nonlinear. Second, the station assignment variables are binary. We address the first difficulty in Section III using the recently developed second-order cone programming (SOCP) relaxation of OPF. Fixing any station assignments, the relaxation of OPF is then convex. Sufficient conditions are known that guarantee an optimal solution to the nonconvex OPF problem can be recovered from an optimal one to its relaxation; see [4] and [5] for a comprehensive tutorial and references therein. Even when these conditions are not satisfied, the SOCP relaxation is still often exact for practical radial networks, as confirmed also by our simulations.

The second difficulty can be properly addressed in a centralized fashion. The solution, presented in Section III of this paper, applies generalized Benders decomposition to the mixed integer convex relaxation, and is suitable for cases where the distribution grid, stations, and EVs are managed centrally by the same operator. When the underlying relaxation of OPF is exact, the generalized Benders decomposition computes a global optimum. In Section IV, we illustrate the performance of our centralized solution through simulations. The simulation results suggest that the proposed algorithm is effective and computationally efficient for practical application.

In this centralized solution, the operator needs global information such as grid topology, impedances, operational constraints, background loads, availability of fully charged batteries at each station, locations and states of charge of EVs, etc. It is implementable only in a vertically integrated system like the State Grid operated electric taxi program in China. A second approach is pursued that relaxes the binary station assignment variables to real ones in $[0, 1]$. The resulting approximate problem of joint battery swapping and OPF is a convex problem. This allows us to develop distributed solutions suitable for systems where the distribution grid, stations, and EVs are operated by separate entities that do not share their private information. This will be explained in Part II of this paper.

B. Literature

There is a large literature on EV charging, e.g., optimizing charging schedule for various purposes such as demand response, load profile flattening, or frequency regulation [6]–[8]; architecture for mass charging [9]–[11]; locational marginal pricing for EV [12]; and the interaction between EV penetration and the optimal deployment of charging stations [13].

Sojoudi and Low [14] seem to be the first to jointly optimize EV charging and ac power flow spatially and temporally through semidefinite relaxation. Zhang *et al.* [15] extend the joint OPF-charging problem to multiphase distribution networks and propose a distributed charging algorithm based on the alternating direction method of multipliers. Chen *et al.* [16] decompose the joint OPF-charging problem into an OPF subproblem that is solved centrally by a utility company and a charging subproblem that is solved in a distributed manner by individual EVs through a coordinative valley-filling signal from the utility company. de Hoog *et al.* [17] use a linear model and formulates EV charging on a three-phase unbalanced grid as a receding horizon optimization problem. It shows that optimizing charging schedule can increase the EV penetration that is sustainable by the grid from 10%–15% to 80%. Linearization is also used in [18] to model EV charging on a three-phase unbalanced grid as a mixed-integer linear program. The binarity arises from the fact that an EV is either being charged at its peak rate or off. These papers focus on jointly optimizing power flows and charging for EVs connected to given locations on the grid. A key feature in our paper is the use of EV mobility to explicitly optimize the spatial redistribution of charging loads.

The literature on battery swapping is much smaller. Tan *et al.* [19] propose a mixed queuing network that consists of a closed queue of batteries and an open queue of EVs to model the battery swapping processes, and analyze its steady-state distribution. Yang *et al.* [20] design a dynamic operation model of a battery swapping station and put forth a bidding strategy in power markets. You *et al.* [21] study the optimal charging schedule of a battery swapping station serving electric buses and propose an efficient distributed solution that scales with the number of charging boxes in the station. Sarker *et al.* [22] propose a day-ahead model for the operation of battery swapping stations and use robust optimization to deal with future uncertainty of battery demand and electricity prices. Zheng *et al.* in [23] study the optimal design and planning of a battery swapping station in a distribution system to maximize its net present value, taking into account life cycle cost of batteries, grid upgrades, reliability, operational cost, and investment cost. Zhang and Rao [24] discuss several business models of battery swapping and leasing service in China. To the best of our knowledge, joint optimization of battery swapping and power flows on distribution grids has not been investigated, which however is becoming an emerging practical issue.

II. Problem Formulation

We focus on the scenario where a fleet of EVs and a set of stations operate in a region that is supplied by an active distribution grid. We assume the distribution grid, stations, and EVs are managed centrally by the same operator, e.g., the State Grid in China. Periodically, say, every 15 min, the system determines a set of EVs that should be scheduled for battery swapping, e.g., based on their current states of charge or their requests for battery swapping. At the beginning of the current control interval, the system assigns to each EV in the set a station for battery swapping. It is reasonable to assume that the EVs travel to their assigned stations and finish swapping their batteries before the end of the current interval, since typically the geographic area served by a distribution grid is relatively small—A city substation (50 MVA, 110 kV) has a service radius of 3–5 km, depending on its load density [25]. Under this assumption, station assignments are decoupled across control intervals and this paper focuses on one such interval.

Batteries returned by the EVs start to be charged at the stations immediately.[2] Since we focus on the scheduling of battery swapping, we assume for simplicity that these batteries are charged at the constant rated power for the control interval under study, which contributes to better serving future battery swapping demand as well. Optimizing charging rates over multiple intervals can be integrated with battery swapping if more future information is available, but that is beyond the scope of the current paper. Our goal is to design an assignment algorithm that minimizes a weighted sum of the distance travelled by the EVs for battery swapping and electricity generation cost, while respecting the EVs' range constraints, the operational constraints of the distribution grid, and ac power flow equations.

In the following, we formulate our optimal scheduling problem. A vector x is a column vector and x^T denotes its transpose.

A. Network Model

Consider a single-phase radial distribution network with a connected directed graph $\mathbb{G} = (\mathbb{N}, \mathbb{E})$, where $\mathbb{N} := \{0, 1, 2, \ldots, N\}$ and $\mathbb{E} \subseteq \mathbb{N} \times \mathbb{N}$. Each node in $\mathbb{N}$ represents a bus and each edge in $\mathbb{E}$ represents a distribution line. We assume $\mathbb{G}$ has a radial (tree) topology with bus 0 representing a substation that extracts power from a transmission network to feed the loads in $\mathbb{G}$. We orient the graph, without loss of generality, so that each line points away from bus 0. Denote a line in $\mathbb{E}$ by (j, k) or $j \to k$ if it points from bus j to bus k. The unique parent bus of each bus j (except bus 0) is indexed by $i := i_j$. Let z_{jk} be the complex impedance of line $(j, k) \in \mathbb{E}$. Let $S_{\text{jk}} := P_{\text{jk}} + \mathbf{i}Q_{\text{jk}}$ denote the *sending-end* complex power from bus j to bus k, where P_{jk} and Q_{jk} denote the real and reactive power flows, respectively. Define l_{jk} as the squared magnitude of the complex current from bus j to bus k and v_j as the squared magnitude of the complex voltage phasor of bus j. We assume the voltage v_0 of bus 0 is fixed.

Each bus j has a base load $s_j^b := p_j^b + \mathbf{i}q_j^b$ (excluding the charging loads from stations), where p_j^b and q_j^b denote the real and reactive power, respectively. Each bus j may also have distributed generation $s_j^g := p_j^g + \mathbf{i}q_j^g$. Let s_j denote the net complex power injection given by

$$s_j := \begin{cases} s_j^g - s_j^b - s_j^e & \text{if bus } j \text{ supplies a station} \\ s_j^g - s_j^b & \text{otherwise} \end{cases}$$

where s_j^e denotes the total charging load at bus j. We assume the base loads s_j^b are given and the generations s_j^g and charging loads s_j^e are variables.

We use the *DistFlow* equations proposed by Baran and Wu in [26] to model power flows on the network

$$\sum_{k:(j,k)\in\mathbb{E}} S_{\text{jk}} = S_{\text{ij}} - z_{\text{ij}} l_{\text{ij}} + s_j, \quad j \in \mathbb{N} \tag{1a}$$

$$v_j - v_k = 2\text{Re}\left(z_{\text{jk}}^H S_{\text{jk}}\right) - |z_{\text{jk}}|^2 l_{\text{jk}}, \quad j \to k \in \mathbb{E} \tag{1b}$$

$$v_j l_{\text{jk}} = |S_{\text{jk}}|^2, \quad j \to k \in \mathbb{E} \tag{1c}$$

where z_{jk}^H is the Hermitian transpose of z_{jk}. The equations impose power balance at each bus in (1a), model Ohm's law in (1b), and define branch power flows in (1c). Note that $S_{i0} := 0$ and $l_{i0} := 0$ when bus $j = 0$ is the substation bus, and when bus j is a leaf node of $\mathbb{G}$, all $S_{\text{jk}} = 0$ in (1a). The quantity $z_{\text{ij}} l_{\text{ij}}$ is the loss on line (i, j), and hence $S_{\text{ij}} - z_{\text{ij}} l_{\text{ij}}$ is the *receiving-end* complex power at bus j from bus i.

The complex notation of the *DistFlow* equations (1) is only a shorthand for a set of real equations in the real vector variables $(s, v, l, S) := (p, q, v, l, P, Q) := (p_j, q_j, v_j, l_{\text{jk}}, P_{\text{jk}}, Q_{\text{jk}}, j, k \in \mathbb{N}, (j, k) \in \mathbb{E})$. Equations (1a) and (1b) are linear in these variables, whereas (1c) is quadratic, one of the two sources of nonconvexity in our joint battery swapping and OPF problem formulated below.

The operation of the distribution network must meet certain specifications. The squared voltage magnitudes must satisfy

$$\underline{v}_j \le v_j \le \overline{v}_j, \quad j \in \mathbb{N} \tag{2a}$$

where $\underline{v}_j$ and $\overline{v}_j$ are given lower and upper bounds on the squared voltage magnitude at bus j, respectively. The distributed real and reactive generations must satisfy

$$\underline{p}_j^g \le p_j^g \le \overline{p}_j^g, \quad j \in \mathbb{N} \tag{2b}$$

$$\underline{q}_j^g \le q_j^g \le \overline{q}_j^g, \quad j \in \mathbb{N} \tag{2c}$$

where $\underline{p}_j^g$, $\overline{p}_j^g$, $\underline{q}_j^g$, and $\overline{q}_j^g$ are given lower and upper bounds on the real and reactive power generations at bus j, respectively. The power flows on line (j, k) must satisfy

$$|S_{\text{jk}}| \le \overline{S}_{\text{jk}}, \quad j \to k \in \mathbb{E} \tag{2d}$$

where $\overline{S}_{\text{jk}}$ denotes the capacity of line (j, k).

The model is quite general. If a quantity is known and fixed, then we set both its upper and lower bounds to the given quantity, e.g., for the voltage of the substation bus, $\overline{v}_0 = \underline{v}_0$. If there is no distributed generation at bus j, then $\overline{p}_j^g = \underline{p}_j^g = \overline{q}_j^g = \underline{q}_j^g = 0$.

B. Battery Swapping Scheduling

Let $\mathbb{N}_w := \{1, 2, \ldots, N_w\} \subseteq \mathbb{N}$ denote the set of buses that supply electricity to stations, whose locations are fixed and known. For simplicity, assume there is only one station (or an ensemble of multiple stations) connected to each bus $j \in \mathbb{N}_w$

[2] Typically at stations, each battery is placed in a charging box before being swapped; thus, a returned battery can immediately find its place in a charging box.

and we use j to index both the bus and the station. The batteries at each station are either charging at the constant rated power r or already fully charged and ready for swapping. Denote the total numbers of batteries and fully charged batteries at station j at the beginning of the current control interval by M_j and m_j, respectively. Note that M_j is always fixed, whereas m_j is observed in each interval.

Let $\mathbb{A} := \{1, 2, \ldots, A\}$ denote the set of EVs in the service area that require battery swapping in the current interval. Denote their states of charge as $(c_a, a \in \mathbb{A})$. Let u_{aj} represent the assignment

$$u_{\mathrm{aj}} = \begin{cases} 1, & \text{if station } j \text{ is assigned to EV } a \\ 0, & \text{otherwise} \end{cases}$$

and let $u := (u_{\mathrm{aj}}, a \in \mathbb{A}, j \in \mathbb{N}_w)$ denote the vector of assignments.

The assignments u satisfy the following conditions:

$$\sum_{j \in \mathbb{N}_w} u_{\mathrm{aj}} = 1, \quad a \in \mathbb{A} \tag{3a}$$

$$\sum_{a \in \mathbb{A}} u_{\mathrm{aj}} \le m_j, \quad j \in \mathbb{N}_w \tag{3b}$$

i.e., exactly one station is assigned to every EV and every assigned station has enough fully charged batteries.

The system knows the current location of every EV a and therefore can calculate the distance d_{aj} from its current location to the assigned station j, e.g., by resorting to a routing application (like Google Maps). In the electric taxi case, if EV a is not currently carrying passengers and can go to swap its battery immediately, then d_{aj} is the travel distance from its current location to station j. If EV a must first complete its current passenger run before going to station j, then d_{aj} is the travel distance from its current location to the destination of its passengers and then to station j. The assigned station j must be within each EV a's driving range, i.e.,

$$u_{\mathrm{aj}} d_{\mathrm{aj}} \le \gamma_a c_a, \quad j \in \mathbb{N}_w, a \in \mathbb{A} \tag{3c}$$

where c_a is EV a's current state of charge and γ_a is its driving range per unit state of charge.

Denote the constraint set for u by

$$\mathbb{U} := \{u \in \{0,1\}^{AN_w} \ : u \text{ satisfies } (3)\}.$$

Assumption 1: $\mathbb{U}$ is nonempty. Under Assumption 1, there are enough fully charged batteries in the system for all EVs in $\mathbb{A}$ in the current interval. This can be enforced when choosing the candidate set $\mathbb{A}$ of EVs for battery swapping, e.g., for EVs that can reach the same subset of stations, ranking them according to their states of charge, scheduling as many EVs as possible in an increasing order, upper limited by the number of fully charged batteries at those stations, and postponing remaining EVs to the next interval.

Since every EV produces a depleted battery that needs to be charged at the rated power r, we can express the net power injection $s_j = p_j + \mathbf{i} q_j$ at bus j in terms of the assignments u as

$$p_j = \begin{cases} p_j^g - p_j^b - r\left(M_j - m_j + \sum_{a \in \mathbb{A}} u_{\mathrm{aj}}\right), & j \in \mathbb{N}_w \\ p_j^g - p_j^b, & j \in \mathbb{N} \setminus \mathbb{N}_w \end{cases} \tag{4a}$$

$$q_j = q_j^g - q_j^b, \quad j \in \mathbb{N}. \tag{4b}$$

Let $f_j : \mathbb{R} \to \mathbb{R}$ model the generation cost at bus j, e.g., for a distributed gas generator. We assume all f_js are increasing and convex functions, e.g., quadratic functions [14]–[16]. We are interested in the following optimization problem:

$$\begin{aligned} \min_{\substack{u,s,s^g,\\ v,l,S}} \quad & \sum_{j \in \mathbb{N}} f_j(p_j^g) + \alpha \sum_{a \in \mathbb{A}} \sum_{j \in \mathbb{N}_w} d_{\mathrm{aj}} u_{\mathrm{aj}} \\ \text{s.t.} \quad & (1)(2)(3)(4),\ u \in \{0,1\}^{AN_w} \end{aligned} \tag{5}$$

where $\sum_{a \in \mathbb{A}} \sum_{j \in \mathbb{N}_w} u_{\mathrm{aj}} d_{\mathrm{aj}}$ is the total travel distance of EVs and $\alpha > 0$ is a weight that makes electricity generation cost and travel distance comparable, e.g., the travel cost per unit of distance.

III. Solution

The joint battery swapping and OPF problem (5) is generally difficult to solve because the constraint (1c) is nonconvex, as mentioned above, and the assignments u are discrete. Our solution strategy has two steps.

SOCP relaxation: We first relax the nonconvex constraint (1c) into a second-order cone, i.e., relax the quadratic equality into inequality. Specifically, replace the *DistFlow* equations (1) by

$$\sum_{k:(j,k) \in \mathbb{E}} S_{\mathrm{jk}} = S_{\mathrm{ij}} - z_{\mathrm{ij}} l_{\mathrm{ij}} + s_j, \quad j \in \mathbb{N} \tag{6a}$$

$$v_j - v_k = 2\mathrm{Re}(z_{\mathrm{jk}}^H S_{\mathrm{jk}}) - |z_{\mathrm{jk}}|^2 l_{\mathrm{jk}}, \quad j \to k \in \mathbb{E} \tag{6b}$$

$$v_j l_{\mathrm{jk}} \ge |S_{\mathrm{jk}}|^2, \quad j \to k \in \mathbb{E}. \tag{6c}$$

Then, the SOCP relaxation of the problem (5) is

$$\begin{aligned} \min_{\substack{u,s,s^g,\\ v,l,S}} \quad & \sum_{j \in \mathbb{N}} f_j(p_j^g) + \alpha \sum_{a \in \mathbb{A}} \sum_{j \in \mathbb{N}_w} d_{\mathrm{aj}} u_{\mathrm{aj}} \\ \text{s.t.} \quad & (2)(3)(4)(6),\ u \in \{0,1\}^{AN_w}. \end{aligned} \tag{7}$$

Fixing any assignments $u \in \{0,1\}^{AN_w}$, the problem (7) is a convex problem. It is a relaxation of the problem (5), given u, in the sense that the optimal objective value of the relaxation (7) lower bounds that of the original problem (5). If an optimal solution to the relaxation (7) attains equality in (6c) then the solution is also feasible, and therefore *optimal*, for the original problem (5). In this case, we say that the SOCP relaxation is *exact*. Sufficient conditions are known that guarantee the exactness of the SOCP relaxation; see [4] and [5] for a comprehensive tutorial and references therein. Even when these conditions are not satisfied, the SOCP relaxation for practical radial networks is still often exact, as confirmed also by our simulations in Section IV.

Hence, we will solve (7) instead of (5).

Generalized Benders decomposition: To deal with the discrete variables in (7), we apply generalized Benders decomposition. Benders decomposition was first proposed in [27] for problems where, when a subset of the variables is fixed, the remaining subproblem is a linear program. It is extended in [28] to problems where the remaining subproblem is a convex program. We now apply it to solving (7).

Denote the continuous variables by $x := (s, s^g, v, l, S)$, whereas the discrete variables by u. Denote the objective function by

$$F(x,u) := \sum_{j\in\mathbb{N}} f_j(p_j^g) + \alpha \sum_{a\in\mathbb{A}} \sum_{j\in\mathbb{N}_w} d_{\mathrm{aj}} u_{\mathrm{aj}}.$$

Given any u, $F(x,u)$ is convex in x since f_js are assumed to be strictly convex. Denote the constraint set for x by

$$\mathbb{X} := \left\{x \in \mathbb{R}^{(5|\mathbb{N}|+3|\mathbb{E}|)} : x \text{ satisfies } (2)(6)\right\}$$

and the constraints (4) on (x,u) by $G(x,u) = 0$ while $u \in \mathbb{U}$. Then, the relaxation (7) takes the standard form for generalized Benders decomposition

$$\begin{aligned} \min_{x,u} \quad & F(x,u) \\ \text{s.t.} \quad & G(x,u) = 0,\ x \in \mathbb{X},\ u \in \mathbb{U} \end{aligned} \tag{8}$$

where $F : \mathbb{R}^{(5|\mathbb{N}|+3|\mathbb{E}|)} \times \{0,1\}^{AN_w} \to \mathbb{R}$ is a scalar-valued function, and $G : \mathbb{R}^{(5|\mathbb{N}|+3|\mathbb{E}|)} \times \{0,1\}^{AN_w} \to \mathbb{R}^{2|\mathbb{N}|}$ is a vector-valued constraint function. Fixing any $u \in \mathbb{U}$, (8) is a convex subproblem in x. We now apply generalized Benders decomposition of [28] to (8).

Write (8) in the following equivalent form:

$$\min_u \quad W(u) \quad \text{s.t.} \quad u \in \mathbb{U} \cap \mathbb{W} \tag{9a}$$

where, for a fixed value of u

$$\begin{aligned} W(u) := \min_{x\in\mathbb{X}} \quad & F(x,u) \\ \text{s.t.} \quad & G(x,u) = 0 \end{aligned} \tag{9b}$$

and

$$\mathbb{W} := \{u : G(x,u) = 0 \text{ for some } x \in \mathbb{X}\}. \tag{9c}$$

The problem (9b), called the slave problem, is convex and much easier to solve than (8). The set $\mathbb{W}$ consists of all us for which (9b) is feasible and hence $\mathbb{U} \cap \mathbb{W}$ is the projection of the feasible region of (8) onto the u-space. The central idea of generalized Benders decomposition is to invoke the dual representations of $W(u)$ and $\mathbb{W}$ to derive the following equivalent[3] problem to (9) (see [28, Ths. 2.2 and 2.3]):

$$\begin{aligned} \min_{u\in\mathbb{U}} \quad & \sup_{\mu\in\mathbb{R}^{2|\mathbb{N}|}} \left\{ \min_{x\in\mathbb{X}} \left\{F(x,u) + \mu^T G(x,u)\right\} \right\} \\ \text{s.t.} \quad & \min_{x\in\mathbb{X}} \left\{\lambda^T G(x,u)\right\} = 0 \quad \forall \lambda \in \mathbb{R}^{2|\mathbb{N}|}. \end{aligned}$$

[3]Assume Slater's condition is always satisfied.

Here λ and μ are Lagrangian multiplier vectors for $\mathbb{W}$ and $W(u)$, respectively. This problem is equivalent to

$$\begin{aligned} \min_{u\in\mathbb{U}, u_0\in\mathbb{R}} \quad & u_0 \\ \text{s.t.} \quad & u_0 \geq \min_{x\in\mathbb{X}} \left\{F(x,u) + \mu^T G(x,u)\right\} \quad \forall \mu \in \mathbb{R}^{2|\mathbb{N}|} \\ & \min_{x\in\mathbb{X}} \left\{\lambda^T G(x,u)\right\} = 0, \quad \forall \lambda \in \mathbb{R}^{2|\mathbb{N}|}. \end{aligned} \tag{10}$$

In summary, the series of manipulations has transformed the relaxation (7) into the master problem (10).

Since (10) has uncountably many constraints with all possible λs and μs, it is neither practical nor necessary to enumerate all constraints in solving (10). Generalized Benders decomposition starts by solving a relaxed version of (10) that ignores all but a few constraints. If a solution to the relaxed version of (10) satisfies all the ignored constraints, then it is an optimal solution to (10) and the algorithm terminates. Otherwise, the solution process of the relaxed version of (10) will identify one μ or λ for which the corresponding constraint is violated. The violated constraint is then added to the relaxed version of (10), and the cycle repeats.

Specifically, the generalized Benders decomposition algorithm for (7) [or equivalently (8)] is as follows.

1) *Step 1:* Pick any $\bar{u} \in \mathbb{U} \cap \mathbb{W}$. Solve the dual problem of (9b) with $u = \bar{u}$ to obtain an optimal Lagrangian multiplier vector $\bar{\mu}$. Let $n_\mu = 1$, $n_\lambda = 0$, $\mu^1 = \bar{\mu}$, and $\mathrm{UBD} = W(\bar{u})$, where n_μ, n_λ are counters for the two types of constraints in (10), and UBD denotes an upper bound on the optimal value of (8).
2) *Step 2:* Solve the current relaxed master problem

$$\begin{aligned} \min_{u\in\mathbb{U}, u_0\in\mathbb{R}} \quad & u_0 \\ \text{s.t.} \quad & u_0 \geq \min_{x\in\mathbb{X}} \left\{F(x,u) + \left(\mu^i\right)^T G(x,u)\right\}, \\ & \qquad i = 1, \ldots, n_\mu \\ & \min_{x\in\mathbb{X}} \left\{\left(\lambda^i\right)^T G(x,u)\right\} = 0 \\ & \qquad i = 1, \ldots, n_\lambda. \end{aligned} \tag{11}$$

Let $(\hat{u}, \hat{u}_0)$ be the optimal solution to (11). Clearly $\hat{u}_0$ is a lower bound on the optimal value of (8) since the constraints in (10) are relaxed to a smaller set of constraints in (11). Terminate the algorithm if $\mathrm{UBD} - \hat{u}_0 \leq \epsilon$, where $\epsilon > 0$ is a sufficiently small threshold.
3) *Step 3:* Solve the dual problem of (9b) with $u = \hat{u}$. The solution falls into the following two cases.
   a) *Step 3a: The dual problem of (9b) has a bounded solution* $\hat{\mu}$, i.e., $W(\hat{u})$ is feasible and finite. Let $\mathrm{UBD} = \min\{\mathrm{UBD}, W(\hat{u})\}$. Terminate the algorithm if $\mathrm{UBD} - \hat{u}_0 \leq \epsilon$. Otherwise, increase n_μ by 1 and let $\mu^{n_\mu} = \hat{\mu}$. Return to *Step 2*.
   b) *Step 3b: The dual problem of (9b) has an unbounded solution*, i.e., $W(\hat{u})$ is infeasible. Determine $\hat{\lambda}$ through a feasibility check problem and its

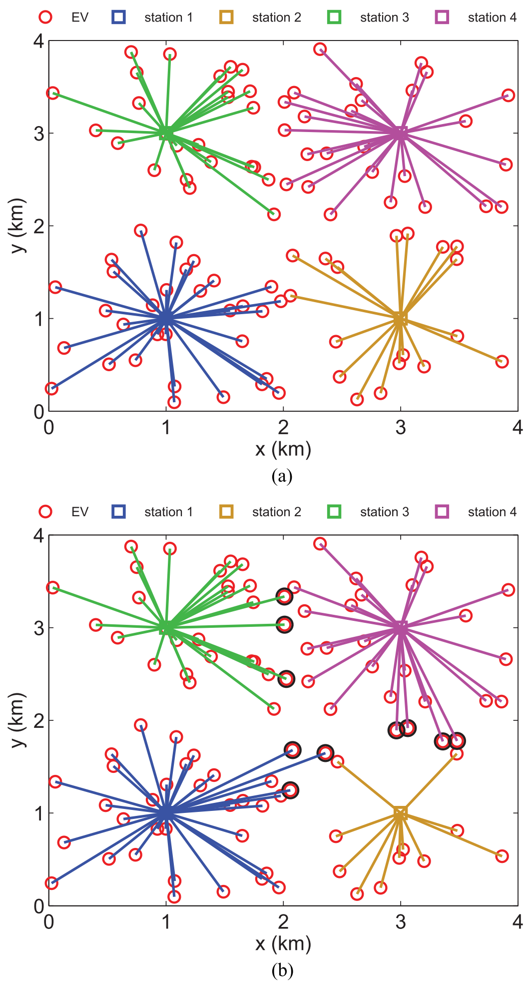


Fig. 1. #EVs=100 (a) Nearest-station policy. (b) Optimal assignments.

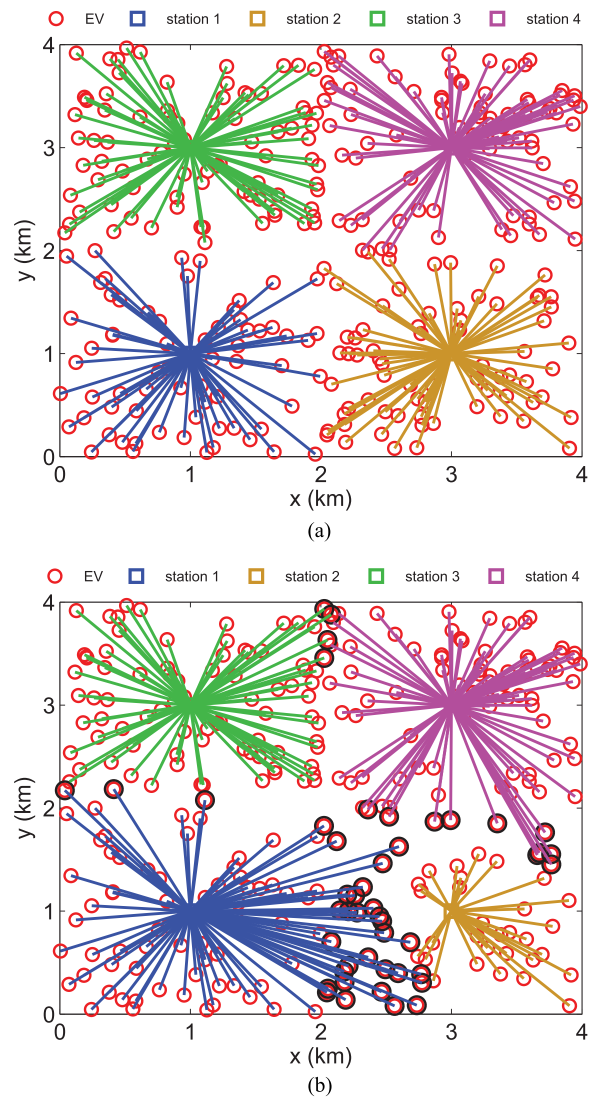


Fig. 2. #EVs=300 (a) Nearest-station policy. (b) Optimal assignments.

dual [29]. Increase n_λ by 1 and let $\lambda^{n_\lambda} = \hat{\lambda}$. Return to *Step 2*.

We make three remarks. First, the slave problem (9b) is convex and hence can generally be solved efficiently. The relaxed master problem (11) involves discrete variables and is generally nonconvex, but it is much simpler than the original problem (8). Second, for our problem, (11) turns out to be a mixed-integer linear program in essence because both F and G are separable functions in (x, u) of the form

$$F(x,u) =: F_1(x) + F_2(u)$$
$$G(x,u) =: G_1(x) + G_2(u)$$

where F_2 and G_2 are both linear in u. Indeed the constraints in (11) are

$$u_0 - F_2(u) - \left(\mu^i\right)^T G_2(u) \geq \min_{x\in\mathbb{X}} \left\{F_1(x) + \left(\mu^i\right)^T G_1(x)\right\} \quad i = 1, \ldots, n_\mu$$
$$\left(\lambda^i\right)^T G_2(u) = -\min_{x\in\mathbb{X}} \left(\lambda^i\right)^T G_1(x) \quad i = 1, \ldots, n_\lambda$$

where the left-hand side is linear in u and the right-hand side is independent of u. Hence, in each iteration, the algorithm solves (11), which is a simplified mixed-integer linear program (always with only one continuous auxiliary variable), and (9b), which is a convex program. Third, every time Step 2 is entered, one additional constraint is added to (11). This generally makes (11) harder to compute but also a better approximation of (10). It is proved in [28, Th. 2.4] that the algorithm will terminate in finite steps since $\mathbb{U}$ is discrete and finite.

IV. Numerical Results

We now evaluate the proposed algorithm through simulations using a 56-bus distribution feeder of Southern California Edison (SCE) with a radial structure. A maximum voltage deviation of 0.05 p.u. is allowed and all line capacities are set to infinity. More details about the feeder can be found in [30, Fig. 2, Table I]. We add four distributed generators and four stations

TABLE I
SETUP

(a) Distributed generator					
Bus	$\overline{p}_j^g$	$\underline{p}_j^g$	$\overline{q}_j^g$	$\underline{q}_j^g$	Cost function
1	4	0	2	-2	$0.3{p^g}^2 + 30p^g$
4	2.5	0	1.5	-1.5	$0.1{p^g}^2 + 20p^g$
26	2.5	0	1.5	-1.5	$0.1{p^g}^2 + 20p^g$
34	2.5	0	1.5	-1.5	$0.1{p^g}^2 + 20p^g$

(b) Station			
Bus	Location	M_j	m_j
5	(1,1)	m_j	A
16	(3,1)	m_j	A
31	(1,3)	m_j	A
43	(3,3)	m_j	A

at different buses, with parameters given in Table I(a).[4] The four stations are assumed to be uniformly located in a 4 km × 4 km square area supplied by the feeder, as shown in Table I(b). Suppose in a certain control interval, there are A EVs that request battery swapping (A will vary in our case studies). Their current locations are generated in a uniformly random manner within the square area while their destinations are ignored. We use the Euclidean distance for d_{aj}. For convenience, we set $M_j = m_j = A,\ j \in \mathbb{N}_w$, which means in each station batteries are all fully charged and sufficient to serve all EVs. We assume all EVs have sufficient battery energy to reach any of the four stations, which means (3c) is readily satisfied. The extension to the general case where each EV has a limited driving range and can only reach some of the stations is straightforward. The constant charging rate is $r = 0.01$ MW [31] at all stations. We set the weight α to be 0.02$/km first [32]. For each case, we conduct ten simulation runs with random EV locations. All numerical tests are run on a laptop with Intel Core i7-3632QM CPU@2.20 GHz, 8-GB RAM, and 64-b Windows 10 OS.

Nearest-station policy: Without optimization, the default policy is that all EVs head for their nearest stations to swap batteries. This is shown in Figs. 1(a) and 2(a) for two specific cases with 100 and 300 EVs, respectively. In practice, this myopic policy can lead to a shortage in fully charged batteries at a station if many EVs cluster around that station due to correlations in traffic patterns. Moreover, it can cause voltage instability: the voltage magnitudes of some buses drop below the threshold 0.95 p.u. in the 300-EV case, as shown in Table II where the last column exhibits the resulting charging load at each bus.

Optimal assignments: Figs. 1(b) and 2(b) show the optimal assignments computed using the proposed algorithm for the above two cases, respectively. The nearest stations are not assigned to some of the EVs (marked black in the figures) when grid operational constraints such as voltage stability are taken into account. The number of such EVs is larger in the 300-EV case than that in the 100-EV case. The tradeoff between the EVs' travel distance and electricity generation cost is optimized. The

[4]The units of the real power, reactive power, cost, distance, and weight in this paper are MW, Mvar, $, km and $/km, respectively.

TABLE II
PARTIAL BUS DATA UNDER NEAREST-STATION POLICY (300 EVs)

Bus	$\lvert V_j \rvert$ (p.u.)	p_j^g	q_j^g	$r\sum_{a\in\mathbb{A}} u_{\mathrm{aj}}$
1	1.050	0.571	0.000	/
4	1.047	2.500	0.663	/
5	1.031	/	/	0.660
16	0.941	/	/	0.700
18	0.948	/	/	/
19	0.944	/	/	/
26	1.050	2.500	0.410	/
31	1.020	/	/	0.830
34	1.044	2.500	1.500	/
43	1.015	/	/	0.810

TABLE III
PARTIAL BUS DATA UNDER OPTIMAL ASSIGNMENTS (300 EVs)

Bus	$\lvert V_j \rvert$ (p.u.)	p_j^g	q_j^g	$r\sum_{a\in\mathbb{A}} u_{\mathrm{aj}}$
1	1.050	0.520	0.000	/
4	1.048	2.500	0.590	/
5	1.025	/	/	0.990
15	0.981	/	/	/
16	0.974	/	/	0.300
17	0.980	/	/	/
18	0.973	/	/	/
19	0.969	/	/	/
26	1.050	2.500	0.439	/
31	1.019	/	/	0.840
34	1.044	2.500	1.500	/
43	1.013	/	/	0.870

OPF results of the 300-EV case are listed in Table III (compare with Table II). As we can see from Table III, the outputs (2.500 MW) of the distributed generators at buses 4, 26, and 34 have reached their full capacity (2.5 MW), whereas the injection (0.520 MW) at bus 1 (the substation bus) is far from its capacity (4 MW). This is consistent with our intuition that distributed generations that are closer to users and potentially cheaper than power from the transmission grid are favored in OPF. Under the optimal assignments, the deviations of voltages from their nominal value are all less than 5%.

Optimality of generalized Benders decomposition: The upper and lower bounds on the optimal objective values for the above two cases are plotted in Fig. 3 as the algorithm iterates between the master and slave problems. More iterations are required for larger scale cases where the algorithm usually struggles longer to obtain an initial feasible solution. Once a feasible solution is found, the gap between the upper and lower bounds starts to shrink rapidly and the convergence to optimality is achieved within a few iterations.

Exactness of SOCP relaxation: We check whether the solution computed by generalized Benders decomposition attains equality in (6c), i.e., whether the solution satisfies power flow equations and is implementable. Our result confirms the exactness of the SOCP relaxation for most cases we have tested on, including the above two. Due to space limit, only partial data of the 300-EV case are shown in Table IV.

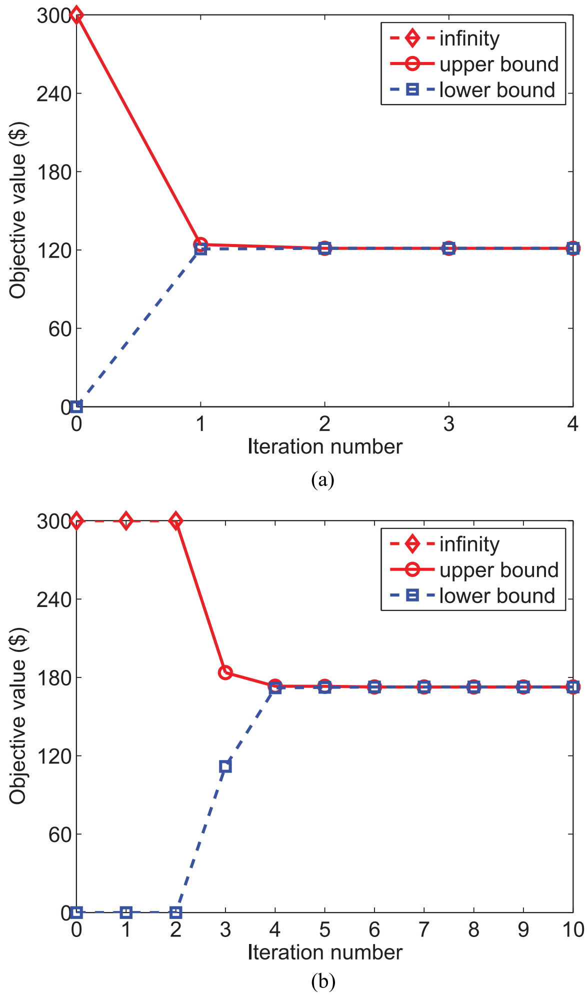


Fig. 3. Convergence of generalized Benders decomposition. (a) #EVs=100. (b) #EVs=300.

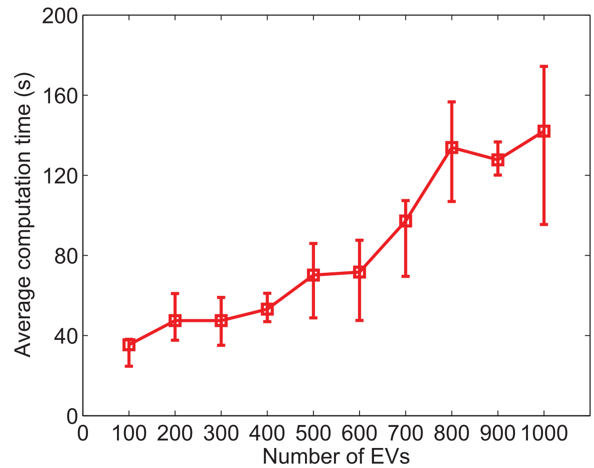


Fig. 4. Average computation time as a function of #EVs.

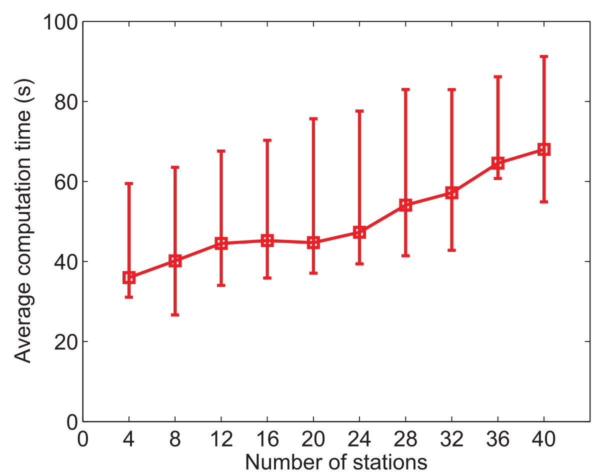


Fig. 5. Average computation time as a function of #stations.

TABLE IV
EXACTNESS OF SOCP RELAXATION (PARTIAL RESULTS FOR 300 EVs)

Bus From	Bus To	$v_j l_{\mathrm{jk}}$	$\lvert S_{\mathrm{jk}}\rvert^2$	Residual
1	2	0.271	0.271	0.000
2	3	0.006	0.006	0.000
2	4	0.202	0.202	0.000
4	5	1.369	1.369	0.000
4	6	0.005	0.005	0.000
4	7	1.952	1.952	0.000
7	8	1.691	1.691	0.000
8	9	0.009	0.009	0.000
8	10	1.269	1.269	0.000
10	11	1.092	1.092	0.000

In summary, SOCP relaxation and generalized Benders decomposition seem to be effective in solving exactly our joint battery swapping and OPF problem (5).

Computational effort: To demonstrate the potential of the proposed algorithm for practical application, we check its required computational effort by counting its computation time for different numbers of EVs and stations, since the number of discrete variables in the optimization problem is the computational bottleneck. We use Gurobi to solve the master problem (integer programming) and SDPT3 to solve the slave problem (convex programming) on the MATLAB R2012b platform.

On one hand, Fig. 4[5] shows the average computation time required by the proposed algorithm to find a global optimum for different numbers of EVs, given the four fixed stations. On the other hand, we fix the number of EVs at 100 and scale up stations that are located at different randomly picked buses. Fig. 5 shows the average computation time of the proposed algorithm grows accordingly, but its sensitivity to the number of stations is moderate as the iterations that struggle for an initial feasible solution (recall Fig. 3) do not increase a lot when the number of EVs is fixed. Therefore, overall the required computational effort is desirable.

Benefit: Fig. 6 displays the average relative reduction in the objective value with different αs using our algorithm,

[5]Each data point in Figs. 4–8 is an average over ten simulation runs with random EV locations.

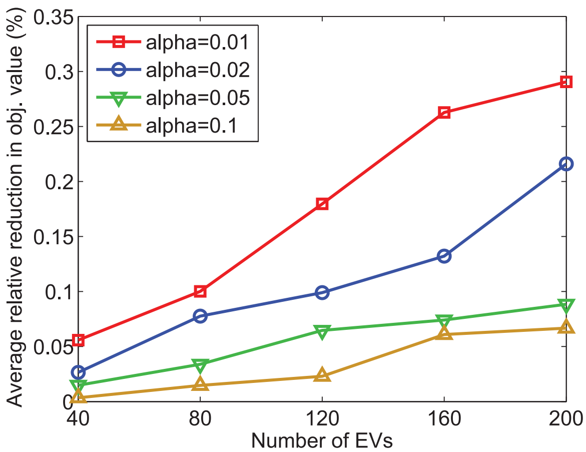


Fig. 6. Average relative reduction in objective value.

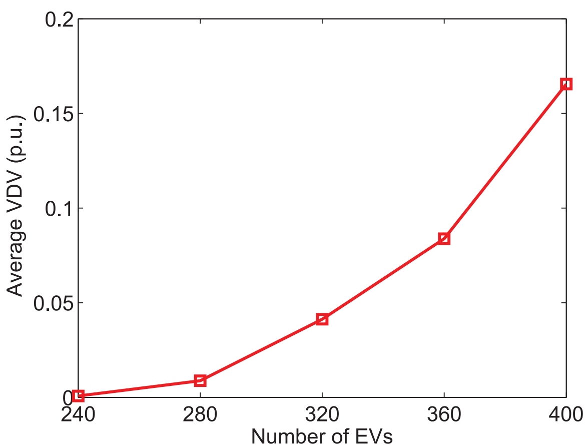


Fig. 7. Average VDV under nearest-station policy.

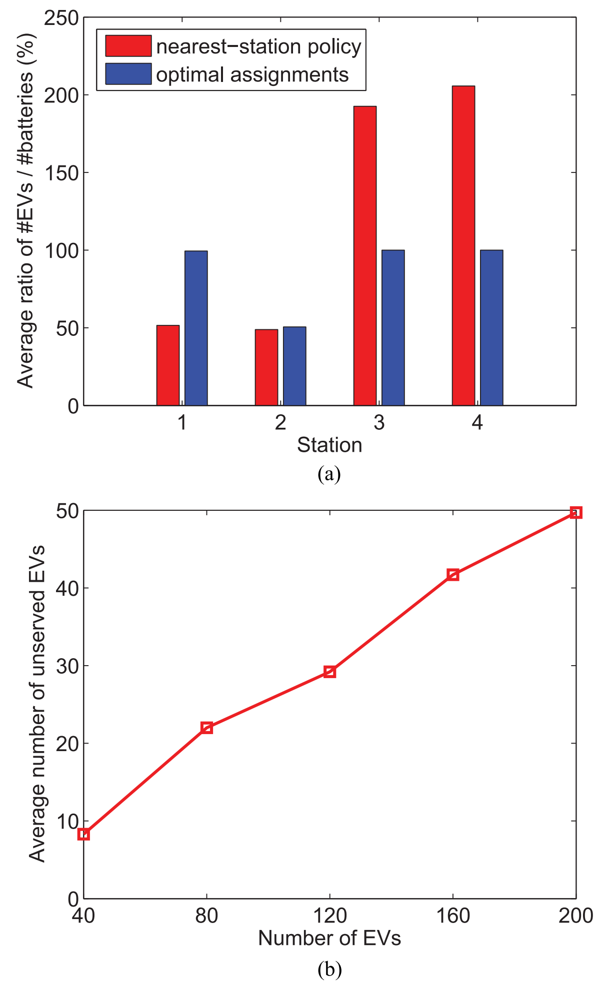


Fig. 8. (a) Average ratio of the number of forthcoming EVs to that of fully charged batteries. (b) Average number of unserved EVs under nearest-station policy.

compared with the nearest-station policy. Scheduling flexibility is enhanced with more EVs, thus improving the savings. In addition, α expresses the system's relative emphasis on the two objective components. Clearly the smaller the weight α on EVs' travel distance is, the more benefit the proposed algorithm provides over the nearest-station policy. However, Fig. 6 also suggests that the improvement is small, i.e., the nearest-station policy is good enough if it is implementable.

The nearest-station policy is sometimes infeasible either when there are more EVs nearest to a station than fully charged batteries at that station or when some operational constraints of the distribution network are violated. In our case studies, infeasibility is mainly due to some voltages dropping below the allowable lower limit. Define a metric *voltage drop violation* as $\mathrm{VDV} := \sum_{j\in\mathbb{N}} \max\{\sqrt{\underline{v}_j} - \sqrt{v_j}, 0\}$ to quantify the degree of voltage violation. Fig. 7 shows the average VDV for the number of EVs ranging from 240 to 400 under the nearest-station policy. The voltage violation becomes more severe when the number of EVs increases.

It is also interesting to look at cases where there are more EVs nearest to a station than fully-charged batteries that station can provide, which, as far as we know, are common in practice. We reset $M_1 = m_1 = M_2 = m_2 = \frac{1}{2}A$ and $M_3 = m_3 = M_4 = m_4 = \frac{1}{8}A$ to simulate these situations. Hence, the total number of fully-charged batteries in the system is $\frac{5}{4}A$. Fig. 8(a) shows, for each station, the average ratio of the number of EVs that go to the station for battery swapping to that of fully charged batteries at the station, under both the nearest-station policy and optimal assignments. In total, 99.40% of station 1's batteries, 50.60% of station 2's batteries, and all the batteries at stations 3 and 4 are used under the optimal assignments, thus they have collectively served all A EVs. Under the nearest-station policy, however, only 51.55% and 48.89% of stations 1 and 2's batteries, respectively, (i.e., a total of around $\frac{1}{2}A$ batteries) are used for swapping. At either of stations 3 and 4, the number of EVs is approximately double that of available fully charged batteries (192.61% and 205.62%, respectively). Fig. 8(b) shows the average number of unserved EVs under the nearest-station policy as a function of the total number of EVs. On average, approximately one in four EVs cannot be served at their nearest stations, mainly due to congestion at stations 3 and 4, whereas available fully charged batteries at stations 1 and 2 are not fully utilized.

V. Conclusion

Summary: We formulate an optimal scheduling problem for battery swapping that assigns to each EV a best station to swap its depleted battery based on its current location and state of charge. The schedule aims to minimize a weighted sum of EVs' travel distance and electricity generation cost over both station assignments and power flow variables, subject to EV range constraints, grid operational constraints, and ac power flow equations. We propose a centralized solution that relaxes the nonconvex constraint of OPF into a second-order cone and then applies generalized Benders decomposition to handle the binary nature of station assignments. Numerical case studies on the SCE 56-bus distribution feeder show the SOCP relaxation is mostly exact and generalized Benders decomposition computes an optimal solution efficiently (with exact SOCP relaxation).

Extension to Part II: As aforementioned, the centralized solution proposed in this paper is applicable to vertically integrated systems where global information and controllability are available. Motivated by the vision of cyber-physical systems to decentralize everything, Part II of this paper summarizes our distributed solutions that schedule battery swapping without revealing the respective pivotal information of the distribution grid, stations, and EVs.

Model limitations: First, Assumption 1 is imposed by choosing a proper candidate set $\mathbb{A}$ of EVs when there is overwhelming demand of battery swapping, which significantly eases the model complexity at the sacrifice of a little performance. It shall be interesting to further model the waiting cost of EVs when they cannot be immediately served at stations. *Second*, optimizing charging rates across intervals can be integrated to form a multi-interval scheduling problem if a good estimate of future information is available. Then, it is worth evaluating the value of future information in improving the overall performance.

References

[1] C2ES, "Climate TechBook," Center for Climate and Energy Solutions, Arlington, VA, USA, 2016. [Online]. Available: www.c2es.org/energy/use/transportation

[2] R.-C. Leou, C.-L. Su, and C.-N. Lu, "Stochastic analyses of electric vehicle charging impacts on distribution network," *IEEE Trans. Power Syst.*, vol. 29, no. 3, pp. 1055–1063, May 2014.

[3] T. Shang, Y. Chen, and Y. Shi, "Orchestrating ecosystem co-opetition: Case studies on the business models of the EV demonstration programme in China," in *Electric Vehicle Business Models*. New York, NY, USA: Springer, 2015, pp. 215–227.

[4] S. H. Low, "Convex relaxation of optimal power flow, I: Formulations and relaxations," *IEEE Trans. Control Netw. Syst.*, vol. 1, no. 1, pp. 15–27, Mar. 2014.

[5] S. H. Low, "Convex relaxation of optimal power flow, II: Exactness," *IEEE Trans. Control Netw. Syst.*, vol. 1, no. 2, pp. 177–189, Jun. 2014.

[6] Z. Ma, D. Callaway, and I. Hiskens, "Decentralized charging control of large populations of plug-in electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 1, pp. 67–78, Jan. 2013.

[7] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 940–951, May 2013.

[8] A. O'Connell, D. Flynn, and A. Keane, "Rolling multi-period optimization to control electric vehicle charging in distribution networks," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 340–348, Jan. 2014.

[9] S. Chen and L. Tong, "iEMS for large scale charging of electric vehicles: Architecture and optimal online scheduling," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2012, pp. 629–634.

[10] J. Rivera, P. Wolfrum, S. Hirche, C. Goebel, and H.-A. Jacobsen, "Alternating direction method of multipliers for decentralized electric vehicle charging control," in *Proc. IEEE Conf. Decis. Control*, 2013, pp. 6960–6965.

[11] J. Rivera, C. Goebel, and H. A. Jacobsen, "Distributed convex optimization for electric vehicle aggregators," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1852–1863, Jul. 2017.

[12] R. Li, Q. Wu, and S. S. Oren, "Distribution locational marginal pricing for optimal electric vehicle charging management," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 203–211, Jan. 2014.

[13] Z. Yu, S. Li, and L. Tong, "On market dynamics of electric vehicle diffusion," in *Proc. 52nd Annu. Allerton Conf. Commun., Control, Comput.*, 2014, pp. 1051–1057.

[14] S. Sojoudi and S. H. Low, "Optimal charging of plug-in hybrid electric vehicles in smart grids," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, 2011, pp. 1–6.

[15] L. Zhang, V. Kekatos, and G. B. Giannakis, "Scalable electric vehicle charging protocols," *IEEE Trans. Power Syst.*, vol. 32, no, 2, pp. 1451–1462, 2017.

[16] N. Chen, C. W. Tan, and T. Q. Quek, "Electric vehicle charging in smart grid: Optimality and valley-filling algorithms," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 6, pp. 1073–1083, Dec. 2014.

[17] J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 365–375, Jan. 2015.

[18] J. Franco, M. Rider, and R. Romero, "A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2200–2210, Sep. 2015.

[19] X. Tan, B. Sun, and D. H. Tsang, "Queueing network models for electric vehicle charging station with battery swapping," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2014, pp. 1–6.

[20] S. Yang, J. Yao, T. Kang, and X. Zhu, "Dynamic operation model of the battery swapping station for EV (electric vehicle) in electricity market," *Energy*, vol. 65, pp. 544–549, 2014.

[21] P. You, Z. Yang, Y. Zhang, S. H. Low, and Y. Sun, "Optimal charging schedule for a battery switching station serving electric buses," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3473–3483, Sep. 2016.

[22] M. R. Sarker, H. Pandžić, and M. A. Ortega-Vazquez , "Optimal operation and services scheduling for an electric vehicle battery swapping station," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 901–910, Mar. 2015.

[23] Y. Zheng, Z. Y. Dong, Y. Xu, K. Meng, J. H. Zhao, and J. Qiu, "Electric vehicle battery charging/swap stations in distribution systems: Comparison study and optimal planning," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 221–229, Jan. 2014.

[24] X. Zhang and R. Rao, "A benefit analysis of electric vehicle battery swapping and leasing modes in China," *Emerg. Markets Finance Trade*, vol. 52, no. 6, pp. 1414–1426, 2016.

[25] Q. Wang, K. Qin, and D. Chen, "Power supply radius optimization for substations with large capacity transformers," 2014. [Online]. Available: http://www.cqvip.com/read/read.aspx?id=83887068504849524852484852

[26] M. E. Baran and F. F. Wu, "Optimal capacitor placement on radial distribution systems," *IEEE Trans. Power Del.*, vol. 4, no. 1, pp. 725–734, Jan. 1989.

[27] J. F. Benders, "Partitioning procedures for solving mixed-variables programming problems," *Numerische Mathematik*, vol. 4, no. 1, pp. 238–252, 1962.

[28] A. M. Geoffrion, "Generalized Benders decomposition," *J. Optim. Theory Appl.*, vol. 10, no. 4, pp. 237–260, 1972.

[29] P. You, Z. Yang, M. Y. Chow, and Y. Sun, "Optimal cooperative charging strategy for a smart charging station of electric vehicles," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2946–2956, Jul. 2016.

[30] M. Farivar, R. Neal, C. Clarke, and S. Low, "Optimal inverter VAR control in distribution systems with high PV penetration," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, 2012, pp. 1–7.

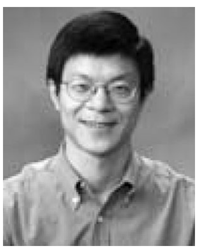
[31] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Trans. Power Electron.*, vol. 28, no. 5, pp. 2151–2169, May 2013.

[32] EIA, "Annual energy review," Energy Information Administration, U.S. Dept. Energy, Washington, DC, USA, 2011. [Online]. Available: www.eia.doe.gov/emeu/aer

Pengcheng You (S'14) received the B.S. degree in electrical engineering from Zhejiang University, Hangzhou, China, in 2013, and the Bachelor's degree (Hons.) in science and engineering from Chu Kochen Honors College, Zhejiang University, in 2013. He is currently working toward the Ph.D. degree in the College of Control Science and Engineering, Zhejiang University.

He was a Visiting Student at Singapore University of Technology and Design and California Institute of Technology, and also a Ph.D. intern in the Pacific Northwest National Laboratory. His research interests include smart grid and machine learning.

Dr. You is a member of the Networked Sensing and Control Group in the State Key Laboratory of Industrial Control Technology, Zhejiang University.



Steven H. Low (F'08) received the B.S. degree from Cornell University, Ithaca, NY, USA, in 1987, and the Ph.D. degree from the University of California at Berkeley, Berkeley, CA, USA, both in EE, in 1992.

Since 2000, he has been a Professor in the Department of Computing and Mathematical Sciences and the Department of Electrical Engineering, California Institute of Technology, Pasadena, CA, USA. Before that, he was with the AT&T Bell Laboratories, Murray Hill, NJ, USA, from 1992 to 1996, and at the University of Melbourne, Melbourne, VIC, Australia, from 1996 to 2000. His research on communication networks was accelerating more than 1 TB of Internet traffic every second in 2014.

Dr. Low was a corecipient of IEEE best paper awards, on the editorial boards of major journals in networking and power systems, and Honorary/Chair Professors in Australia, China, and Taiwan. He was a member of the Networking and Information Technology Technical Advisory Group for the U.S. President's Council of Advisors on Science and Technology in 2006.

Wayes Tushar (S'06–M'13) received the B.Sc. degree in electrical and electronic engineering from Bangladesh University of Engineering and Technology, Dhaka, Bangladesh, in 2007, and the Ph.D. degree in engineering from Australian National University, Canberra, ACT, Australia, in 2013.

He is currently an Advanced Queensland Research Fellow in the School of Information Technology and Electrical Engineering, University of Queensland, Brisbane, QLD, Australia. His research interests include energy and storage management, renewable energy, smart grid, design thinking, and game theory.

Guangchao Geng (S'10–M'14) received the B.S. and Ph.D. degrees in electrical engineering from the College of Electrical Engineering, Zhejiang University, Hangzhou, China, in 2009 and 2014, respectively.

He is currently a Research Assistant Professor in the College of Electrical Engineering, Zhejiang University. Before joining the Faculty of Zhejiang University, he conducted research at Iowa State University, Ames, IA, USA, and University of Alberta, Edmonton, AB, Canada. His research interests include power system stability and control, power system measurement, and renewable energy integration.

Chau Yuen (SM'12) received the B.Eng. degree in EEE and Ph.D. degree in wireless communications from Nanyang Technological University, Singapore, in 2000 and 2004, respectively.

In 2005, he was a Postdoctoral Fellow with Lucent Technologies Bell Labs, Murray Hill, NJ, USA. In 2008, he was a Visiting Assistant Professor at Hong Kong Polytechnic University. From 2006 to 2010, he was with the Institute for Infocomm Research, Singapore, as a Senior Research Engineer. Since 2010, he has been an Assistant Professor at Singapore University of Technology and Design, Singapore.

Dr. Yuen is an Associate Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. In 2012, he received the IEEE Asia–Pacific Outstanding Young Researcher Award.

Zaiyue Yang (M'10) received the B.S. and M.S. degrees from the Department of Automation, University of Science and Technology of China, Hefei, China, in 2001 and 2004, respectively, and the Ph.D. degree from the Department of Mechanical Engineering, University of Hong Kong, Hong Kong, in 2008, all in automatic control.

He was a Postdoctoral Fellow and Research Associate with the Department of Applied Mathematics, Hong Kong Polytechnic University, before joining the College of Control Science and Engineering, Zhejiang University, Hangzhou, China, in 2010. Then, in 2017, he joined the Department of Mechanical and Energy Engineering, Southern University of Science and Technology, Shenzhen, China, where he is currently a Professor. His research interests include smart grid, signal processing, and control theory.

Prof. Yang is an Associate Editor of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS.

Youxian Sun received the Diploma in chemical engineering from the Department of Chemical Engineering, Zhejiang University, Hangzhou, China, in 1964.

In 1964, he joined the Department of Chemical Engineering, Zhejiang University. From 1984 to 1987, he was an Alexander Von Humboldt Research Fellow and Visiting Associate Professor at the University of Stuttgart, Stuttgart, Germany. Since 1988, he has been a Full Professor at Zhejiang University. In 1995, he was elevated to an Academician of the Chinese Academy of Engineering. His research interests include modeling, control, and optimization of complex systems, and robust control design and its applications. He has authored/coauthored more than 450 journal and conference papers. He is currently the Director of the Institute of Industrial Process Control and the National Engineering Research Center of Industrial Automation, Zhejiang University.

Prof. Sun is the President of the Chinese Association of Automation, and was the Vice-Chairman of IFAC Pulp and Paper Committee and the Vice-President of the China Instrument and Control Society. He is an IFAC Fellow.