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A two-stage stochastic optimization model for scheduling electric vehicle charging loads to relieve distribution-system constraints

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ABSTRACT

Electric vehicles (EVs) hold promise to improve the energy efficiency and environmental impacts of transportation. However, widespread EV use can impose significant stress on electricity-distribution systems due to their added charging loads.

This paper proposes a centralized EV charging-control model, which schedules the charging of EVs that have flexibility. This flexibility stems from EVs that are parked at the charging station for a longer duration of time than is needed to fully recharge the battery. The model is formulated as a two-stage stochastic optimization problem. The model captures the use of distributed energy resources and uncertainties around EV arrival times and charging demands upon arrival, non-EV loads on the distribution system, energy prices, and availability of energy from the distributed energy resources. We use a Monte Carlo-based sample-average approximation technique and an L-shaped method to solve the resulting optimization problem efficiently. We also apply a sequential sampling technique to dynamically determine the optimal size of the randomly sampled scenario tree to give a solution with a desired quality at minimal computational cost.

We demonstrate the use of our model on a Central-Ohio-based case study. We show the benefits of the model in reducing charging costs, negative impacts on the distribution system, and unserved EV-charging demand compared to simpler heuristics. We also conduct sensitivity analyses, to show how the model performs and the resulting costs and load profiles when the design of the station or EV-usage parameters are changed.

1. Introduction

Electric vehicles (EVs) hold great promise to improve the energy efficiency and environmental impacts of transportation. However, widespread EV use brings uncertain impacts to electric power systems, especially at the distribution level. Clement-Nyns et al. (2010) find that uncontrolled EV charging (*i.e.*, EVs charging without any coordination) can result in power losses and voltage deviations on the local distribution network. Razeghi et al. (2014) study the impacts of charging 10 EVs in an uncontrolled fashion on a residential transformer. They demonstrate that the resulting charging loads can result in catastrophic failure of the transformer and conclude that management of charging loads is critical for prolonging trans-

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former life. Weiller (2011) estimates the impacts of EV recharging using standard wall outlets on electric loads in the United States. The results of this analysis show that residential, workplace, and retail-shopping-center loads can be increased by 74%.

One way to accommodate these impacts of widespread EV use is to upgrade distribution-system infrastructure, including transformers. This solution would see the distribution system sized to accommodate the anticipated peak load. Indeed, because distribution-infrastructure investments are typically long-lived (*e.g.*, most distribution transformers have a design life of 20.5 years), the system would be sized based on anticipated future peak loads. This is an inefficient solution, however, because the peak load on many distribution circuits may only be reached a few hours each year. This means that the distribution system would have excess unused capacity the overwhelming majority of the time. Uncontrolled EV charging may exacerbate this inefficiency, because uncontrolled EV charging tends to give the distribution load profile more extreme peaks.

An alternate solution is control or management of EV-charging loads. The basic premise of charging control is that an EV may be connected to a charging station for a longer duration of time than is required to fully recharge its battery. If so, the charging demand could be shifted within this window of time. By properly managing such flexible EV loads, the peaks in the distribution load profile can be reduced, alleviating the need for expensive transformer upgrades. Moreover, controlling EV charging can increase the load factor of the distribution system, meaning that the distribution infrastructure is used more efficiently.

The literature typically focuses on two forms of EV-charging control: centralized and decentralized. Decentralized control is a price-signal based method to coordinate EV charging. This method usually requires individual EVs and an EV aggregator to communicate their demands for charging energy and the availability of energy in an iterative before reaching an equilibrium. In this context, an equilibrium is a set of charging loads that are optimal from the perspective of the EVs (*i.e.*, it satisfies their demands for charging energy) and the EV aggregator (*i.e.*, the aggregator can feasibly serve the charging loads). Ma et al. (2013) introduce a price-based decentralized control scheme. In their proposal, EVs communicate their charging demands iteratively based on a set pricing scheme. They demonstrate that the iterative scheme can reach an equilibrium under mild conditions. Wu et al. (2012) propose a decentralized scheme which uses a price policy that encourages individual EVs to provide frequency regulation. Bayram et al. (2013) propose an admission-control mechanism that applies congestion pricing to mitigate station-level overloads and guarantee quality of service among EVs. Xi and Sioshansi (2014) introduce a decentralized pricing scheme that conveys both price and quantity from the power system operator to an EV aggregator or to individual EVs.

Conversely, centralized control relies on a single entity to manage EV charging. Thus, it relies on EV owners letting someone else determine when their vehicles are recharged. Sathaye (2014) proposes an optimization framework for an electrified taxi-service operator to schedule taxi-charging loads. This approach takes the optimality and feasibility of the transportation system into account, assuming a Level-2 DC charging station and that the power system can always fulfill the station's charging demand. This approach taken by Sathaye (2014) differs from many other works examining charging management. Sathaye (2014) assumes that the power system can always serve charging loads and optimizes charging from the perspective of the taxi service. Many other works, conversely, focus on optimality and feasibility, taking into account that the power system may not be able to accommodate charging loads that are not properly managed. For instance, Hu et al. (2014) introduce a linear programming model that determines an optimal EV-charging schedule to minimize charging cost to an EV aggregator while preventing distribution-system congestion. Rotering and Ilić (2011) propose a dynamic programming model to control and optimize accumulated EV-charging demand. Sundström and Binding (2012) develop a quadratic programming model that minimizes the operation cost of an EV aggregator's operation cost while imposing distribution-network constraints.

More recent works pay increasing attention to uncertainty in when EVs may arrive at a charging station and their charging demands upon arrival. Pantoš (2012) proposes a stochastic optimization model with uncertainty in EV-usage patterns to create strategies for an individual EV that wants to participate in energy and ancillary service markets by providing charging flexibility. Momber et al. (2015) introduce an EV-charging control model for a risk-averse EV aggregator. They use conditional value-at-risk as the risk metric in the objective function. Their work focuses on modeling uncertainty in EV-usage patterns and energy prices.

The use of stochastic optimization techniques typically raises computational challenges, because of the immense number of scenarios needed to capture all of the uncertainties modeled. Pantoš (2012) and Momber et al. (2015) deal with this issue through scenario reduction, wherein a large starting set of scenarios is reduced to a smaller set that is meant to represent the range of possible sample paths in the starting set of scenarios. This use of scenario reduction raises two important and related questions, however. The first is whether scenario reduction guarantees a high-quality solution. The second is how to choose appropriate starting and reduced sample sizes that give a desired solution quality with the least amount of computational effort. This second issue is especially important if a charging-control model is to be used for actual real-time control of EV-charging loads.

In this paper we introduce a centralized control model that concentrates on high-power fast-charging stations. The aim of the model is to optimize EV-charging loads within a fixed window of time after each EV arrives at the charging station to minimize costs. The costs modeled include a penalty, based on the associated accelerated aging, of operating the distribution transformer above its rated capacity. The core methodology of our approach is a two-stage stochastic optimization problem. We model uncertainties in EV-arrival times and charging demands upon arrival. The model also captures uncertainties in