Electric Power Systems Research 145 (2017) 166–174

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Fuzzy Optimization for the Operation of Electric Vehicle Parking Lots

Samy Faddel*, Ali T. Al-Awami, M.A. Abido

Department of Electrical Engineering, King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia

ARTICLE INFO

Article history:
Received 11 August 2016
Received in revised form 5 November 2016
Accepted 4 January 2017

Keywords:
Electric vehicles
Parking lot
Fuzzy optimization
EV mobility uncertainty

ABSTRACT

Integrating electric vehicles (EVs) into the smart grid has become a topic of great interest lately due to the potential benefits it provides. Since EVs are expected to be parking most of the time, it is expected that EVs will play a role in competitive business environments like parking lots (PLs). However, the parking lot operator (PLO) is exposed to many uncertainties, including those associated with the electric energy market and EV mobility. This paper proposes a fuzzy optimization model that aims at maximizing the PLO's profit while satisfying EV owners' charging requirements. It is assumed that the PLO bids EV charging schedules in the day-ahead market of energy. The PLO can, then, balance any deviation from its day-ahead schedule in the real-time market. The uncertainties of the profits due to market price fluctuations are taken into consideration. Also, the uncertainties associated with the EV mobility, such as the EV type mix using the parking lot (PL), their initial and final states of charge, and their departure time, are also considered. In addition, the effect of the charging efficiency is investigated. The simulation results show that the proposed fuzzy optimization algorithm leads to higher realized profits than those of the deterministic benchmark algorithm. Also, the results show that the proposed algorithm is robust and offers high profitability even with high levels of uncertainty.

1. Introduction

The number of electric vehicles (EVs) to be integrated into the power grid is expected to increase in the coming few years [1]. EVs have many positive benefits. They can help in carbon emission reduction [2], petroleum independence, and the integration of renewable energy resources [3]. However, the anticipation of a large penetration of EVs brings up many technical challenges that need to be addressed. As EVs need more frequent charging than gasoline-powered vehicles due to the limited capacity of their batteries, the associated transportation infrastructure must provide more electric charging stations along the main road networks and at other diverse points [4]. Moreover, drivers need to have their EVs charged within a certain time frame, e.g. before they depart from their offices, their homes, and the like. Hence, charging stations should have the ability to schedule multiple requests having different time constraints, charging rates, and power consumption dynamics [4,5]. As a result, problems related to the process of charging a random number of EV batteries with random energy demands need to be addressed.

Potential benefits of EV scheduling to different stakeholders using data collected from over 2000 non-residential electric vehicle supply equipment (EVSEs) were investigated in Ref. [6]. It was shown that up to 24.8% decrease in the aggregate monthly bill was possible, and the aggregated peak load was reduced with median peak shed values around 30–42% for each month. The effect of multiple EV charging on the distribution transformer was addressed in Ref. [7]. It was suggested that the off peak tariff would have an effect over the EV owners, and the loss of life of the transformer would only be affected after a specified amount of vehicles penetration which is relatively high. EV charge control schemes for controlling frequency and voltage and deferring investment were considered in Refs. [8–11].

Different algorithms for reducing peak power demand while satisfying the different constraints specified in each charging request were investigated in Refs. [4,12]. However, the uncertainty of the EV mobility was not considered. A bi-layer optimization of EV scheduling to improve the grid operation and to accommodate renewable energy was proposed in Refs. [13,14]. However, EVs' driving characteristics were not considered.

Uncertainties associated with EV mobility were considered in Refs. [15–17]. In Ref. [15], an algorithm was presented to manage a large number of plug-in hybrid EVs (PHEVs) charging at municipal parking in an optimal way. The algorithm attempts to maximize the average state of charge (SOC) at the next time step

* Corresponding author at: King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia. Fax: +966 13 860 3535.
E-mail address: Samy_Gamal47@yahoo.com (S. Faddel).

http://dx.doi.org/10.1016/j.epsr.2017.01.008
0378-7796/

Nomenclature

IN	Income of the parking lot
C	Cost of the energy bought by parking lot
PT	Expected profits of the parking lot obtained from the optimization
β	Price of energy charged by the parking lot to the customer
ρ	Forecasted day-ahead energy price (¢/kW h).
AV	EV availability (1 for available, 0 for unavailable)
st	Starting time for EV charging
dt	EV Departure time
Δt	Duration of time interval
NEV	Total number of EV charging stations at the parking lot
PC	Parking lot capacity due to transformer rating (kW)
POP	Preferred operating point, i.e. scheduled charging rate
$SOCI$	Initial state of charge
$SOCF$	Required final state of charge
MC	Maximum battery capacity
MR	Maximum charging rate of the EV
EVP	Estimated percentage of EVs remaining after unexpected departure
A_Dep	Accumulated probability of the unexpected departure
λ	Fuzzy objective
μ_x	Membership function
$\tilde{PT}$	Fuzzy set of the profit
$\overline{PT}$	Upper bound of the profit
$\overline{MR}$	Upper bound of the charging rate inequality
$\overline{MC}$	Upper bound of the battery capacity inequality
$\overline{SD}$	Upper bound of the final state of charge inequality
pt	Fuzzy variable associated with the profit inequality
mr	Fuzzy variable associated with the charging rate inequality
mc	Fuzzy variable associated with the battery capacity inequality
sd	Fuzzy variable associated with the final state of charge inequality
K_{PT}	Percentage of uncertainty in the profit
K_{MR}	Percentage of uncertainty in the maximum charging rate
K_{MC}	Percentage of uncertainty between the initial and the battery capacity
K_{SD}	Percentage of uncertainty between the initial and the required final state of charge
i	Index for numbering the EVs
t	Time index
EV	Electric vehicle
PL	Parking lot
PLO	Parking lot operator

taking into consideration uncertainties of the initial SOC, the arrival time and the time for completing the morning commute. Input data were derived from normal distribution curves based on transportation statistical data. However, in order to make real-time decisions based on Ref. [15], a large amount of raw data needs to be processed, which increases computation burden. Multi-stage stochastic model of EVs aggregators was considered in Ref. [16] to participate in day-ahead and intraday electricity markets. The authors addressed the performance of the EVs aggregator in the presence of the demand response exchange. Because stochastic programming involves generating a scenario tree, the computational cost becomes excessively high as the number of uncertain parameters increase. Minimizing the overall load variance in the grid taking into consideration the stochastic nature of the EV availability was considered in Ref. [17]. However, the uncertainties of the initial and required final state of charge were not considered.

In Ref. [18], a hierarchical optimal algorithm was proposed to schedule the charging of EVs to maximize the revenue of the charging service provider while satisfying customer charge demands and transformer capacity constraints. It was assumed that the arrival and departure times and the initial SOC of each EV are all stochastic but with known probability distributions. However, the presented algorithm is quite complicated and the computational burden increases exponentially with the length of the operation horizon and the number of EVs connected to the charging system.

The algorithms presented in Refs. [15–18] concern a utility or an aggregator that serves a large number of EVs. In these cases, the EV characteristics and EV mobility characteristics can be predicted with reasonable accuracy due to the law of large numbers. In contrast, a parking lot operator (PLO) serves a small subset of EVs, which makes their characteristics and EV mobility data much harder to predict. This makes the optimization of EV charging for a PLO a particularly interesting problem. However, few research works have addressed this problem. An algorithm for real-time energy management of a grid-connected PHEVs charging parking lot (PL) was considered in Ref. [19]. It was developed based on statistical and forecasting models to reduce the overall daily cost of PHEVs charging and mitigate the impact of the charging park on the main grid. However, the algorithm does not employ any optimization model to solve the problem.

A centralized EV charge scheduling system for PLs of a city using a realistic vehicular mobility/parking pattern focusing on individual parking lots was presented in Ref. [20]. The approach utilized both day-ahead and real-time scheduling components to maximize the total PL revenues and the total number of EVs fulfilling their requirement. The system starts charging from the time slot in which the buying price is the cheapest irrespective of the EV time availability, which is risky and sub-optimal. In Ref. [21], a stochastic model was developed to generate scenarios indicating the behavior of EVs. For simplicity, it was assumed that only one type of charging stations is available in the system, hence the maximum charging rate is unified. In addition, the EV specifications were assumed to be the same for the whole fleet, which is unrealistic. Furthermore, the uncertainty of the initial SOC was not taken into account.

This work is motivated by the need to address the optimization of EV charge scheduling for a PLO considering EV mobility and market uncertainties while maintaining the problem size tractable. A novel linear fuzzy optimization approach is proposed for this purpose. Fuzzy optimization was successfully implemented to various power system problems [22–26] as it can incorporate the uncertainties while maintaining the problem tractable [27]. To the best of the authors' knowledge, fuzzy optimization has never been used for dealing with the uncertainties associated with EV mobility.

The aim of the formulated optimization problem is to maximize the profits of the PLO while satisfying the EV owners' requirements. Unlike most of the fuzzy applications reported in the literature [23,24,26], the proposed fuzzy optimization approach is based on fuzzifying (i.e. defining a membership function for each of) the problem uncertain constraints rather than the problem uncertain parameters. This simplifies the optimization problem and reduces substantially its complexity. Specifically, the uncertainties associated with the market prices, initial SOCs, maximum battery capacities of the incoming EVs, and final SOCs required by the EV owners at departure are modeled using the proposed linear fuzzy optimization. In addition, unexpected departure times for some EVs