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Robust linear architecture for active/reactive power scheduling of EV integrated smart distribution networks

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ABSTRACT

This paper develops a robust bundled active and reactive power management of EV integrated smart distribution networks. To model the problem, at first, the deterministic formulation of the problem is expressed as a non-linear programing (NLP), which minimizes the difference between the energy cost and the revenue of EVs' (parking lot's) reactive power exchange with the network as the objective function, subject to the AC power flow equations, system operation limits and EVs' characteristics as the problem constraints. Then, while the NLP optimization reveals local optima, the NLP model is converted into a linear programming (LP) model using linearized AC power flow equations. The system uncertainties including active and reactive loads, electrical energy and reactive power prices as well as EVs' charging/discharging schedules are modeled in the proposed linear model. Accordingly, the robust model is implemented and it considers one scenario, namely the most-conservative scenario of the objective function in the main problem. To decrease the calculation time, Benders decomposition (BD) approach is used to speed up the total processing time. The proposed robust linear architecture is tested on three distribution test networks to demonstrate its efficiency and performance. The results show that the NLP model can be substituted with the high-speed LP model. Moreover, the computation speed is improved by using the BD method. In addition, the capacity of the injected power of EVs is reduced in the most-conservative scenario in comparison with the deterministic model's scenario, while the consumed power of loads and EVs have been increased in this scenario. The proposed robust architecture against uncertainties is shown to yield a more robust solutions at the expense of higher operation cost.

1. Introduction

Wide deployment of electric vehicles (EVs) is perceived to be a viable solution for reducing emissions and partially resolving environmental concerns. EVs can be categorized into two major categories: hybrid EVs (which utilize internal mechanisms in the vehicle to generate and store electricity) and plug-in EVs (which need to be connected to the grid to be charged). Combinations of these categories are also possible, such as plug-in hybrid EVs (known as PHEVs) which take the advantages of both technologies. PHEVs commonly use unidirectional chargers to transfer power from the grid in a way that the active power can be controlled in one direction [1]. These EVs, however, can potentially change the distribution load profile, especially when their penetration rate is high, and accordingly they cause some changes in the distribution network operation such as increasing demanded power of the network, deteriorating voltage profile, and overloading lines [2–4]. Application of bidirectional chargers can be a viable alternative solution to address the mentioned issues as they can improve the operational performance of distribution networks to manage bundled active and reactive powers used by EVs [5–7]. Indeed, EVs that are equipped with bidirectional chargers can facilitate the operation management of distribution systems. This can be achieved by an intelligent coordination of loads and EV scheduling in smart distribution networks. In addition to the considerable complexity, the prevailing uncertainties in the active and reactive powers' prices, load forecast errors and EVs behavior (plug in/out time, stored energy, charge rate, number of EVs connected to the network, etc.) are the important issues of this coordination that should be considered [8].

Robust optimization (RO) methods have some practical advantages in comparison with scenario-based methods. In the case of

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Nomenclature

Variables: All variables are in per unit (pu)

C Cost of imported energy from the upstream network in \$
E^u Uncertainty variable of total required energy in parking lot (EC) in p.u.
P^u, Q^u Uncertainty variable of active and reactive loads
PB Active power of all batteries in the parking lot
PB^u, SE^u Uncertainty variables of PB^{max} and SE^{max}
PE, QE Active and reactive power of parking lot seen from the network
PG, QG Active and reactive power generation or station
PL, QL Active and reactive line flows
PLC, QLC Active and reactive power losses of chargers
QC Total reactive power of chargers in the parking lot
R The revenue of EVs' (parking lot's) reactive power exchange with the network at the study period in \$
V Voltage magnitude
ΔQE, ΔPG Deviations of QE and PG
ΔV, θ Voltage deviation and angle of voltage
λ, $\bar{\mu}$, μ Lagrangian multipliers
ρ^{up}, $\rho^{\overline{uq}}$ Uncertainty variable of ρ^p, ρ^q in \$/MWh and \$/MVArh, respectively
$\Delta\rho^{up}$, $\Delta\rho^{uq}$ Deviations of ρ^{up} and ρ^{uq}

Constants

A Bus incidence matrix (if there is a line between buses b and j, $A_{b,j}$ is equal to 1, otherwise zero)
AER, L All electrical range and distance that EV derives in the electric mode in miles
a_r, a_{im} Coefficients of active power loss of charger
BC, SOC Battery capacity in p.u., and its state of charge
b_r, b_{im} Coefficients of reactive power loss of charger
EC Total required energy in parking lot in p.u.
F^{sub} Incidence matrix of bus and upstream network
g, b Conductance and susceptance of a line in p.u.
TPF Tangent value in minimum power factor point
PB^{max} Charge rate of all batteries in the parking lot in p.u.
PD, QD Active and reactive loads in p.u.
$QE0$ Normal value of QE in p.u.
SE^{max} Charger capacity of all EVs in the parking lot in p.u.
SG^{max} Maximum upstream network capacity in p.u.
SL^{max} Maximum line capacity in p.u.
T_{step}, $\Delta\alpha$ Time step in hour, angle deviation in radian
V^{max}, V^{min} Maximum and minimum voltages in p.u.
ΔV^{max} Maximum voltage deviation in p.u.
ρ^p, ρ^q Electrical energy and reactive power prices in \$/MWh and \$/MVArh, respectively

Sub-indexes

m Line slope in linear term of voltage magnitude
n_b, n_t Numbers of buses and time periods
r Uncertainty level
U Uncertainty set
u_i^b, $\bar{u}_i^b$, $\tilde{u}_i^b$ ith variable, normal (forecasted values of the uncertain parameters) value and deviation value of uncertainty at bus b
$y0$, Δy Normal (forecasted) value and deviation value of variable y (including E^u, P^u, Q^u, PB^u, SE^u, ρ^{up}, ρ^{up} and some of Lagrangian multipliers)
W, S, π The objective function value of the sub-problem, slack and dual variables in the sub-problem in p.u.
Δ^b budget of uncertainty at bus b

Sets and indices

b, t, l, k Indices of bus, time, linearization segments of voltage magnitude term and circular constraint, respectively
φ_b, φ_t, φ_l, φ_k Sets of bus, time, linearization segments of voltage magnitude term and circular constraint, respectively

EV's operation, the RO-based model determines optimal schedules in order to achieve the best operation characteristics, whereas scenario-based methods find optimal schedules according to a limited number of possible uncertainty scenarios. Additionally, unlike scenario-based models, RO-based methods guarantee a predefined level of objective function value. In approaches that parameter uncertainty is modeled using probability and possibility theories, distribution functions are assumed and employed to model and measure the objective functions. Furthermore, fuzzy logic-based models use pre-specified membership functions to model uncertainty. Similarly, the Monte-Carlo simulation based approaches need to guess a probability density function for the uncertain variable based on which the scenarios are generated. Making such assumptions can sometimes lead to non-protective conclusions, as further discussed in Ref. [9]. The RO model, on the other hand, neither requires a particular assumption about the nature of the uncertain parameter, nor enforces any pre-assumption on the size of uncertainty. Indeed, different scenario generation approaches can result in the different solutions especially in stochastic methods. Also, in scenario generation methods, the uncertainty parameter should have a probability distribution function or a specific membership function. In the contrast, in the proposed model, there is no assumptions that involve the above mentioned issues and in this regard, results of these two methods are not comparable.

Various deterministic, stochastic, and robust active power management models can be found in the literature for solving similar problems associated with EVs. A deterministic active power management is presented in Refs. [10–13]. In Ref. [10], the EV penetration rate is increased using charging power management while the objective is to minimize the energy cost. In Ref. [11], the charging management of EVs is used for optimal load management in which the objective function is the load changes minimization. Based on the results of these papers, the EV's penetration rate is increased but the network indices have not been improved. In Refs. [12,13] charging/discharging power management of EVs are used for increasing the EV's penetration rate and improvement of network indices such as voltage profile and power losses. A stochastic active power management in distribution networks is introduced in Refs. [14–16] where Ref. [14] implements the active power of EVs to enhance voltage security in microgrids, while Ref. [15] uses the EVs as storage systems. Ref. [16] presents the stochastic reconfiguration and optimal coordination of V2G plug-in electric vehicles considering correlated wind power generation. However, the active power management is solely used in the paper. The stochastic active and reactive power management in the wholesale reactive power market is introduced in Ref. [17]. Based on Refs. [14–17], the power management capability of EVs paved the way to implement them in the distribution networks for different purposes. Robust active power management is presented in Ref. [18], considering the battery energy as the only source of uncertainty. Finally, in Refs. [19–22], active power management of renewable energy resources and EVs are considered, simultaneously. In order to have a brief comparison on different works in the area, the taxonomy of the proposed methodologies for the EVs integration into the distribu-