Applied Energy 226 (2018) 1087–1099

Contents lists available at ScienceDirect

Applied Energy

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

Optimal planning of electric vehicle charging stations comprising multi-types of charging facilities

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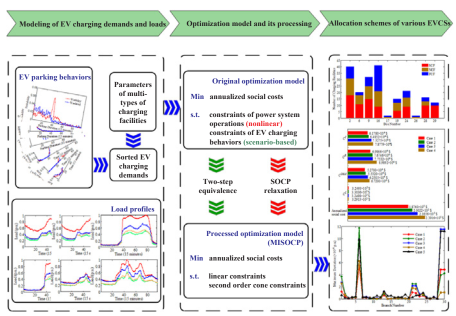
HIGHLIGHTS

- Multi-types of charging facilities are regarded to be mixedly installed in EVCSs.
- An optimization model is proposed to determine the allocation schemes of EVCSs.
- A two-step equivalence is proposed to process the scenario-based constraints.
- An exact SOCP relaxation is adopted to make the optimization model easily solved.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Distribution system
Electric vehicle charging station (EVCS)
Mixed integer second-order cone programming (MISOCP)
Multi-types of charging facilities
Optimal planning
Two-step equivalence

ABSTRACT

Along with the rapid development of electric vehicle (EV) charging technologies, many new types of charging facilities have been utilized in electric vehicle charging stations (EVCSs). Charging facilities with different rated charging power can satisfy the charging demands from diverse EV owners, and simultaneously impact the spatial and temporal distribution of EV charging demands, which in consequence challenges the rationality and economy of EVCS allocation schemes. Based on this background, this paper indicates that EVCSs should be regarded to comprise multi-types of charging facilities during the planning stage, and a new optimization model is proposed for the target of minimizing the annualized social cost of whole EV charging system. To process the complexity of the optimization model, a two-step equivalence is proposed and applied. After the equivalence and some exact relaxation, the proposed optimization model has been transformed into the type of mixed integer second-order cone programming (MISOCP), which can be efficiently solved by appropriate mathematical methods. To demonstrate the feasibility and effectiveness of the proposed approach, a practical urban area fed by a 31-bus distribution system in China has been used as the test system and the numerical results are presented and analyzed.

1. Introduction

AS a great substitute for traditional fossil fuel-powered transportation, electric vehicles (EVs) featured with low greenhouse gas emission and high energy utilization efficiency have attracted rapidly increased attention during the past decade [1,2]. Based on this background, EV advocates (e.g. governments, automobile companies and energy corporations) have made great efforts to promote the popularization of

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https://doi.org/10.1016/j.apenergy.2018.06.014
Received 27 March 2018; Received in revised form 11 May 2018; Accepted 1 June 2018
0306-2619/

Nomenclature

Sets and indices

k Index of EVs
n Index of land blocks
t Index of time segments
s Index of seasons
i/j Index of buses
$u(i)/u(j)$ Set of downstream buses connected with bus i/j
$v(j)$ Set of upstream buses connected with bus j
Ω_N Set of buses in the distribution system
Ω_L Set of branches in the distribution system
Ω_C Set of candidate buses for EVCSs

Parameters

$P^{SCF/NCF/FCF}$ Rated charging power of SCF/NCF/FCF (kW)
Cap_k Battery capacity of EV numbered k (kWh)
SOC_k State of charge of EV numbered k
T_k^{dur} Parking duration of EV numbered k (h)
N_b Quantity of land blocks in the certain area
N_{bus} Quantity of buses in the distribution system
$c^I_{SCF/NCF/FCF}$ Investment cost for each SCF/NCF/FCF ($)
d Discount rate
y_{CF} The economic life of charging facility (year)
c^R Per-unit grid reinforcement cost ($/kW)
$c^{O\&M}_{SCF/NCF/FCF}$ Annual O&M cost for each SCF/NCF/FCF ($)
c^L Per-unit cost of network losses ($/kWh)
R_{ij}/X_{ij} Resistance/reactance of branch from i to j (Ω)
Δt Span of each time segment (h)
$U_{\min}/U_{\max}$ Permitted minimum/maximum limit of voltage magnitude (kV)
$I_{ij,\max}$ Upper limit of branch current from i to j (A)
$d(i, j)$ Distance between bus i and bus j (km)
$d_{\lim}$ Permitted maximum limit of EV's extra travel distance for charging (km)

Variables

P_{EV_k} Charging demand of EV numbered k (kW)
C^I Annualized investment cost of EVCSs ($)
C^R Annualized grid reinforcement cost ($)
$C^{O\&M}$ Annual O&M cost of EVCSs ($)
C^L Annual network losses cost ($)
$C^{L-W}_{s,t}/C^{L-WD}_{s,t}$ Network losses cost in time segment t of season s related with workdays/weekends ($)
R_d Auxiliary variable in annualization
$N_i^{SCF/NCF/FCF}$ Integer variable that indicates the installation number of SCF/NCF/FCF at bus i
$C^L_{s,t}$ Unified representation of $C^{L-W}_{s,t}$ and $C^{L-WD}_{s,t}$
I_{ij} Branch current from i to j at the designated time segment (A)
P_{ij}/Q_{ij} Active/reactive power in branch from i to j at the designated time segment (kW/kVar)
U_i Voltage magnitude at bus i under the designated time segment (kV)
$N_{ij}^{SCF/NCF/FCF}$ Quantity of EVs whose destinations are bus i but recharge at bus j via SCF/NCF/FCF
P_j^{Load}/Q_j^{Load} Active/reactive load demand at bus j under the designated time segment (kW/kVar)
P_j^{EV} EV charging power at bus j under the designated time segment (kW)
$N_i^{ar\_SCF/NCF/FCF}$ Quantity of EVs whose destinations are bus i and prefer charging via SCF/NCF/FCF
$\overline{U_i}$, $\overline{I_{ij}}$ Auxiliary variable in SOCP relaxation
Δ_{ij} Deviation variable used in exactness verification of SOCP relaxation

EVs. It is anticipated that EV penetration will meet a swift growth in the foreseeable future [3]. However, unlike the expeditious refueling of traditional fossil fuel-powered vehicles, EV recharging activities require appropriate charging facilities, as well as certain length of charging time [4]. These inconveniences are world-wide pain points of the booming EV industry and in consequence bring negative impacts on EVs' social acceptance [5,6]. To improve EV charging efficiency and relieve the described pain points, the optimal planning of EVCSs is becoming an extremely important topic. An optimal allocation scheme of EVCSs can satisfy the charging demands from diverse EV owners with minimum social costs, and thereby promote the development of EV industry.

The optimal planning of EVCSs has been investigated in the literatures from different perspectives. Firstly, viewed from the modeling of EV charging demands, various approaches have been proposed and utilized. In [7] and [8], EV charging demands are assumed to be constants, which is a simple and convenient way except for the sacrifice of accuracy. In [9], voltage fluctuations in power systems have been taken into consideration and EV charging demands are described to be voltage-dependent. For the sake of considering the influence of traffic flow, origin-destination (OD) analysis has been introduced to model the transportation behaviors of EV users in [10,11] and thereby the distributions of EV charging demands are derived. In [12] and [13], EV charging actions are divided into two types: destination charging and urgent charging. The specific charging demands corresponding to each type of charging action are forecasted according to the historical data of EV parking behaviors and the forecasting approach is essentially a kind of Monte Carlo simulation method [14]. Secondly, in terms of the planning scenarios, various factors and targets have been considered in the previous researches. In [15], the optimal number, location and capacity of each EVCS are determined to satisfy the growth of EV penetration with the target of maximizing the profit of electrical distribution companies. In [16], peak/off-peak electricity price and adequate incentives for EV owners are considered to make the planning scenario more practical. In [17], the concept of vehicle-to-grid (V2G) is introduced to the planning of EVCSs, which brings a significant reduction in the operational costs of the distribution network. Furthermore, the optimization model is embedded with time-of-use demand response programs in [18], where the benefits of EVs' appropriate charging/discharging scheduling are exhibited in a comprehensive manner. In [19], load profile templates for different seasons, as well as workdays/weekends are integrated in the optimization model, and EVCSs are jointly planned with distribution network topology. In [20], the optimal planning of EVCSs is considered as a multi-objective problem, during which the overall annual costs of investment and energy losses are minimized simultaneously with the maximization of annual traffic flow captured by EVCSs. Thirdly, reviewed from the aspect of solution algorithms, the frequently used algorithms in existing studies can be divided into two types: heuristic algorithms and mathematical algorithms. On the whole, heuristic algorithms are relatively more popular than mathematical algorithms, because the planning problems of EVCSs are always embedded with the complicated driving and parking behaviors of EV owners, which make the optimization models extremely complex and only few of them can be successfully solved by mathematical algorithms. As the representatives of heuristic algorithms, genetic algorithm (GA) [21,22], particle swarm optimization (PSO) [23], GA-PSO hybrid algorithm [24], differential evolution (DE) [25] and chemical reaction optimization (CRO) [26] are frequently