



Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates



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HIGHLIGHTS

- Electric vehicle (EV) charging station planning considers the effect of power and transportation systems.
- Traffic data is utilized to benchmark the obtained behaviors of EVs.
- Load templates are used to reflect the uncertain states of distribution networks.
- Traffic and load capability constraints are integrated into the planning model.

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ABSTRACT

This paper develops a novel solution to integrate electric vehicles and optimally determine the siting and sizing of charging stations (CSs), considering the interactions between power and transportation industries. Firstly, the origin–destination (OD) traffic flow data is optimally assigned to the transportation network, which is then utilized to determine the capacity of charging stations. Secondly, the charging demand of charging infrastructures is integrated into a cost-based model to evaluate the economics of candidate plans. Furthermore, load capability constraints are proposed to evaluate whether the candidate CSs deployment and tie line plans could be adopted. Different scenarios generated by load profile templates are innovatively integrated into the economic planning model to deal with uncertain operational states. The models and framework are demonstrated and verified by a test case, which offers a perspective for effectively realizing optimal planning of the CSs considering the constraints from both transportation and distribution networks.

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1. Introduction

Driven by the low carbon target, many countries have considered the electrification of transportation as one of national strategic plans and key investment areas [1–6]. As a novel distributed mobile resource, electric vehicles (EVs) are becoming a vital part for smart grid development. Charging infrastructures are the essential connection between EVs and the corresponding power system. Thus, appropriate planning of charging infrastructures is fundamental for promoting fast development of EVs while guaranteeing the normal operation of the power system. So, in this paper, how to economically plan the charging infrastructures, particularly charging stations (CSs), is studied and discussed.

Charging load estimation or forecasting is the basis for the planning of the charging infrastructures. The charging load profile was

estimated in [7] by a Markov decision process, while Monte Carlo simulation based on probability distribution functions was investigated in [8]. The models were mainly from the temporal view. Moreover, a spatial–temporal model (STM) was proposed in [9] to evaluate the impact of large-scale deployment of EVs on the distribution network. The model ran based on the systematic integrations of power and transportation system analysis. An origin–destination (OD) analysis was also utilized in the model to reflect the spatial and temporal characteristics of EV charging stations. Considering multiple factors, such as oil price, social demand, battery development, etc., system dynamic and multi-agent methods were proposed in [10] to obtain more comprehensive results. The above literature provided methods for charging load estimation or forecasting from different aspects. However, not all the method could be fit for CS planning. The charging load used for planning would be aggregated by the profiles directly from EVs or reflected by other quantities, like the traffic flow, in a typical operational mode.

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Nomenclature

Scalars and parameters

b	is a parameter for the BPR function
N_D	is the set of buses in the distribution network
L_D	is the set of lines in the distribution network
N_T	is the set of nodes in the transportation network
L_T	is the set of links in the transportation network
d_{m-n}	is the distance between CSs at node m and n
$d^{\min}$	represents the allowed minimum distance between any CS pair
t_a^0	is the free-flow travel time for road a
c_a	is the traffic capacity of road a
b, v	are the retardation factor, respectively
Ω	is the set of candidate CS nodes in the T-network
Δt	is the predicted time interval
H	is the typical daily charging times of vehicles in the planning area
ω	is the average ratio of daily charging in CS
ε_t	is the normalized traffic flow coefficient, in time period t , to reflect the daily charging ratio
μ	is the average service rate of charging device
p_0	is the free probability of the CS that EV can get charged by a charging service
$W_q^{\max}$	is the maximum average waiting time
$s^{\min}, s^{\max}$	are the lower and upper limits for the number of the charging devices in each CS, respectively
r_0	is the interest rate
m_C	is the capital recovery coefficient for the CSs
M	is the total number of the scenarios
$C_i^{\text{CS-fix}}, C_i^{\text{CS-var}}$	are the fixed and variable investment of the CS at bus i , respectively
δ^S	is the unit operation cost for substations
δ^{loss}	is the unit cost for the power loss
D	is the days of the target year
g_{ij}	is the conductance of line ij
ψ_L, ψ_C	are the bus sets for the lines, and the candidate CSs in the distribution network
P_{Bi}	represents the base value for the load profile
$N_{k,i}$	is the number of the k th type of the classes at bus i
$\sigma_{k,t,m}$	is the profile coefficient of the k th type classes in the time period t for scenario m
$P_{Li,t,m}$	represents the conventional active load demand at bus i in time period t
$P_{i,t}^{\text{CP}}$	represents the charging demand from the charging points (CPs) at bus i in time period t
$Q_{i,t,m}^S$ and $Q_{Li,t,m}$	are reactive power of the substation and the conventional reactive load demand at bus i in time period t , respectively
$V^{\min}, V^{\max}$	are the lower and upper limits for the voltage magnitude, respectively
$p_{ij}^{\max}$	is the upper limit of the power flow at line ij
P_i^{S-0}	is the capacity of the substation at bus i , if $x_i^S = 0, P_i^{S-0} = 0$
N_B	is the total number of buses
N_S	is the number of the substations
N_L	is the number of lines in operation
ϖ	is the working efficiency of the charging device ($0 < \varpi \leq 1$)
P_{CD}	is the charging capacity of a charging device
P_{CP}	is the charging rate of a CP
κ	is the service ability of a CP (vehicles/day)
γ	is the vacant rate ($0 \leq \gamma \leq 1$)

$\eta_{i,t}$	is the normalized parking demand coefficient to reflect the charging demand of the CPs at bus i in time period t
τ_i	is the weight factor for the i th objective, if all objectives share the same weight, then $\tau_i = 1$

Variables

fr_a	is the traffic flow on road a
$t_a(fr_a)$	is the road impedance function, mainly indicating the travel time for road a
fp_k^{ru}	is the traffic flow on path k connecting the original-destination (OD) pair $r-u$
q_{ru}	is the total traffic flow between the OD pair $r-u$.
$\delta_{a,k}^{rs}$	is the 0–1 variable reflecting whether road a is included in path k connecting the OD pair $r-u$
$\lambda_{j,t}$	is the equivalent average arrival rate at node j in time period t
$fn_{j,t}$	is the traffic flow captured by the CS at node j in the time period t , which can be obtained through the sum of the corresponding fr_a with the same injection direction
ρ	is the average service rate of the CS
S	is the number of available charging devices
W_q	is the average waiting time.
β	is the average service rate of a charging device. It is noted that β should be less than 1.0, to guarantee the statistic equilibrium for the operation of the system
x_i^{CS}	is the binary variable for indicating the state of CSs in the D-network. If a candidate CS exists at bus i and is included in the final solution, $x_i^{\text{CS}} = 1$, otherwise 0
F_c	is the total cost
C_{CS}	is the annual investment for CSs
C_{sub}	is the annual operation cost of the substations
C_{loss}	is the annual cost for the power loss
$P_{i,t,m}^S$	is the power output of the substation at bus i in time period t in the m th scenario
$V_{i,t,m}$	is the voltage magnitude at bus i in time period t in the m th scenario
$\theta_{ij,t,m}$	is the phase angle deviation of line ij in time period t in the m th scenario
x_i^S	is the binary variable for indicating the state of substations. If a substation exists at bus i , $x_i^S = 1$, otherwise 0
x_{ij}^L	is the binary variable for indicating the state of lines. If line ij is in the final solution, $x_{ij}^L = 1$, otherwise 0
$G_{ij}(x_{ij}^L)$ and $B_{ij}(x_{ij}^L)$	are the real and imaginary item of the nodal admittance matrix, respectively. The matrix is closely affected and determined by the state of $B_{ij}(x_{ij}^L)$
$P_{i,t}^{\text{CS}}$	represent the charging demand from the CSs at bus i in time period t
$P_{ij,t,m}$	is the power flow at line ij in time period t in the m th scenario
$x_j^{\text{CS-T}}$	is the binary variable for indicating the state of CSs in the T-network. If $x_{j*}^{\text{CS}} = 1$ (j^* is the corresponding bus to node j in the coupled network), $x_j^{\text{CS-T}} = 1$, otherwise 0
$F_{ij}(x)$	is the value of the i th objective function in the j th candidate plan
$F_i(x^*)$	is the best value based on the i th objective function
F_i^W	is the worst value based on the i th objective function
N_p	is the number of the available plans
$F_{ij}(x)$	is the i th objective value in the j th plan
$Bl_j(x)$	is the bargaining value for the j th plan

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