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Modelling and assessment of the combined technical impact of electric vehicles and photovoltaic generation in radial distribution systems

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A B S T R A C T

Photovoltaics (PVs) provide new opportunities for radial distribution systems (RDSs) that feed electric vehicle charging stations (EVCSs). However, the accurate assessment of the combined technical impact is problematic because of the uncertainties of sources/loads. In previous research, we developed a technique to assess the impact of PV generation. This new study presents a general analytical technique (GAT) that evaluates the combined impact for an extended time frame. Specifically, the GAT effectively assesses the fulfilment of technical requirements for weekly RDS operating variables as specified in regulations. As our main objective is to improve the assessment accuracy of the EV and PV interaction in RDSs, the weekly assessment was extended to a one-year time period, during which it is possible to capture the total uncertainty. Also, correlation of input variables is handled.

The computational cost of the GAT is lower than that associated with Monte-Carlo simulation, which is used to confirm the GAT accuracy. Although the results focus on an RDS located in Spain, GAT is applicable to any RDS and is scalable to different penetration levels. The numerical results show the impact of different correlated and non-correlated case studies on the voltage profile, apparent power flow in lines, and real loss.

1. Introduction

The development of electric vehicles (EVs) is currently driven by the need to decrease reliance on foreign oil supplies and CO_2 emissions [1,2]. However, their large-scale use involves the massive integration of EVCSs in traditional RDSs. This integration involves numerous technical challenges [3,4]. One of the most important challenges concerns the heterogeneous sources that generate the power for EVCSs. CO_2 emissions can be reduced by the inclusion of renewable power in these RDSs [1,2,4] (e.g. PV power). Although renewable power in RDSs with EVCSs makes the generating system more sustainable [3,4], the assessment of this interaction is problematic because of the inherent uncertainties associated with the sources/loads involved. Precisely for this reason, this issue has not as yet been successfully addressed. Moreover, the uncertainty parameters may have a considerable level of correlation.

Many probabilistic studies have analysed the potentially negative technical impacts of EVCSs on RDSs such as the following: (i) transformer and cable thermal loading [5–10]; (ii) stability and node voltage profile [5,8,11–17]; (iii) power line losses [5,10,15]; (iv) system power demand [9,14–21]; (v) system reliability and costs [22–24]; (vi) harmonics and unbalance [10]. Similar probabilistic work analysed how PV units produced various adverse technical impacts on RDSs [20,25–28].

Until now, the negative technical impacts of EVCSs or PV units have been minimized by demanding interconnection requirements (EVCS [4] and PV [29]), which are based on probabilistic assessments for worst-case scenarios, i.e. peak load or any other representative snapshot (e.g. PV units [30–32]). These probabilistic assessments limited to one or only a few snapshots provide the statistical characterization (PDF and CDF) for each snapshot or time interval; however, they do not reflect the aggregated statistical behaviour over a longer time period [33].

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Nomenclature

List of symbols

a_{i_i}	real constants
$\boldsymbol{C}$	multivariable input random variable of the RDS
COP	Copula
d	any given day of the week$(d = 1, \ldots, 7)$
d	daily distance covered by an EV
d_r	maximum range of an EV
$\boldsymbol{E}(\boldsymbol{E}')$	initial SOC of the battery at the beginning of a recharge cycle, being $\boldsymbol{d}(\boldsymbol{L_1})$ the the distance covered by the EV
E	discrete SOC of the battery
$f_{\boldsymbol{C}_i}(\boldsymbol{C_i})$	PDF of the continuousunivariate random variable $\boldsymbol{C_i}$
$f^*_{\boldsymbol{C}_i}(\boldsymbol{C_i})$	PMF of the discrete univariate random variable $\boldsymbol{C_i}$
$F_{\boldsymbol{C}_i}(\boldsymbol{C_i})$	CDF of the univariate random variable $\boldsymbol{C_i}$ $\left(F_{\boldsymbol{C}_i}(\boldsymbol{C_i}) = \int_{-\infty}^{\infty} f_{\boldsymbol{C_i}}(\boldsymbol{C_i}) d\boldsymbol{C_i}\right)$
$F^{-1}_{\boldsymbol{C}_i}$	inverse distribution function of the univariate random variable$\boldsymbol{C_i}$
$g_{\boldsymbol{t}'_k}(\boldsymbol{t}'_{\boldsymbol{k}})$	PDF of the random variable EV parking duration
$G_{ij}(B_{ij})$	real (imaginary) part of the element in the bus admittance matrix
$\boldsymbol{G_{g\_\beta}}$	global irradiance on a β tilted surface
$G_{\boldsymbol{t}'_k}(\boldsymbol{t}'_{\boldsymbol{k}})$	CDF of the random variable EV parking duration
$\boldsymbol{H_g}(\boldsymbol{H_d})$	$(\boldsymbol{H_d})$ global (diffuse) irradiation
$h_{\boldsymbol{t_k}}(\boldsymbol{t_k})$	PDF of the random variable charging start time of the EV battery
i, j, k	any given number
$K_{\boldsymbol{C}}(\xi)$	cumulant-generating function of random variable $\boldsymbol{C}$
$\boldsymbol{k_d}$	hourly diffuse fraction
$\boldsymbol{K_t}$	daily clearness index
$\boldsymbol{L_i}(\boldsymbol{l_i})$	distance travelled of the *i*th trip for an EV in km (p.u.)
$M_{\boldsymbol{C}}(\xi)$	moment-generating function of random variable $\boldsymbol{C}$
m	any given month$(m = 1, \ldots, 12)$
n	any given RDS node
n_n	number of RDS nodes
n_d	any given commercial load node of the RDS
n_{ev}	number of RDS nodes with EV
n_f	number of lines of the RDS
n_{il}	any given industrial load node of the RDS
n_l	number of RDS nodes with load
n_s	sample size
n_{p_k}	any given RDS node with a representative parking lot
n_{pv}	number of RDS nodes with a PV unit
n_{rl}	any given residential load node of the RDS
n_{rv}	random variable number
N_c	number of 10-min intervals required for full charging process of the EV battery
P_{ev}	discrete charging power level of the EV battery
$\boldsymbol{P_{ev_i}}$	charging power of an*i*th single EV
$P^{\diamond}_{ev}$	continuous charging power of the EV battery
$P_g(Q_g)$	real (reactive) generation power of a traditional generator
$\boldsymbol{P_{loss}}$	total real loss in the RDS
$\boldsymbol{P_l}(\boldsymbol{Q_l})$	real (reactive) load power
$\boldsymbol{P_{pv}}$	PV power
$\boldsymbol{P_{tev}}$	total charging power for a given set of EVs
q	any given10-min interval in a day $(q = 1, \ldots, 144)$
r	any given number
$\boldsymbol{S_{f,i-j}}$	apparent power flow in line connecting node *i* and *j*
$\boldsymbol{t_k}$	charging start time of the EV battery
$\boldsymbol{t}'_{\boldsymbol{k}}$	EV parking duration in which the EV battery is charged
t_x	*x*th 10-min interval
t_1	internal time in a full charging process of the EV battery
t_2	time required for a full charging process of the EV battery
$\boldsymbol{U_i}(\boldsymbol{U_{C_i}})$	univariate uniform distribution (associated with random variable $\boldsymbol{C_i}$)