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Probabilistic load flow analysis of photovoltaic generation system with plug-in electric vehicles

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ABSTRACT

This paper performs a probabilistic load flow (PLF) analysis of photovoltaic (PV) generation system with electric vehicles (EVs). The randomness of power generated by PV and the randomness charging profiles of EVs is modeled. Different EV charging behaviors are involved, one is EV charging start time distribution driving by time of use (TOU) electricity tariff, the other is that EV charging power is dispatched for minimizing the minimum equivalent load. The well-established 3 point estimation method (3PEM) is employed to compute load flow variables' statistic moments by deterministic load flow at 3 points selected from each random variable. Application of the PLF model proposed in this paper, in PG&E 69 bus distribution system with daily meteorological data of a city in China, is demonstrated. PV generation connected position is optimized. The results are analyzed for various EV charging scenarios.

Introduction

Probabilistic load flow (PLF) was proposed by Borkiwska in the early 1970s [1]. PLF can analyze steady-state power system's operations characteristics under various possible uncertainties, and has been applied in many areas such as evaluation of reliability, probability simulation, energy loss analysis and transient analysis.

Issues related to energy saving and carbon emission reduction have come to the fore in recent decades. The penetration of renewable energy is increasing in some actual power systems rapidly. The PV generation system is fast increasing with the advance of new materials and new technologies [2], though it leads to serious operational and planning problems due to fluctuations of the climate [3]. Some research works have focused on power supply reliability and voltage variation sensitivity due to the fluctuation of renewable energy such as wind energy and solar energy [4,5]. The weather conditions are taken into account planning renewable energy capacity in Ref. [6] for reducing the cost and satisfying loss of load probability and CO_2 constraints. An optimization framework, presented in [7], is employed for facilitating a prospective investor to attain at an optimal investment plan in large-scale solar PV generation projects. Solar energy has a stochastic nature. In short term, solar energy is generally rich in day time and none in night time, while in the long term, output of solar energy is richer in spring than in winter. Also, meteorological features are not the same in different areas. Photovoltaic (PV) generation power has the possibility of causing significant uncertainty problems in a distribution system concerned, since its total installed capacity is projected to increase at a significant rate [8,9].

Plug-in electric vehicle (EV) poses another new challenge to power system operation [10,11]. Generally speaking, electric vehicles (EVs) are the vehicles fully or partly powered by electricity. As an effective means of reducing carbon emissions and mitigating noise pollution, EVs are becoming increasingly popular in the global motor vehicle market. A large number of plug-in EVs will also introduce significant uncertainty to power system because of their stochastic nature of charging behaviors.

Some research work has been carried out with uncertain factors associated with solar power output and charging power of EVs taken into account. Ref. [12] provides a stochastic mathematical model for EV/PHEV (plug-in hybrid EV) aggregate load. In [13], the charging pattern of plug-in EVs is optimized for minimizing voltage deviation and energy loss with consideration of the random load profile. Monte Carlo simulation (MCS) is employed for simulating PLF with photovoltaic cell in [14]. In [15], a probabilistic load flow tool is constructed in order to provide cumulative density functions of branch power flows, node voltages and active power line losses with a large number of EVs. Three charging scenarios

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are simulated in Ref. [15]. Up to now, less research work has been done on the PV generation system with EVs. The optimized planning of the PV generation system with EVs is not involved in former PLF. The interaction between PV generation and EVs both in time and in space has not yet been discussed.

From the mathematical point of view, PLF can be assorted by simulation method and analytical method. Simulation methods such as MCS [14] and Latin hypercube sampling [16] are relatively computationally expensive and time consuming, compared with analytical methods such as Convolution Approach [1], Cumulant Method (CM) [17], First-Order Second-Moment Method (FOSMM) [18] and point estimation method (PEM) [19,20]. Good results can be achieved with PEM by using deterministic load flow while keeping computational burden low [21,22]. 3 points can reach almost the same precision as multi-points estimation while the computational burden is the same as 2 points estimation [19,20].

Given the above background, PLF of the PV generation system with EVs is proposed in this paper. Both the randomness of PV generation power output and EV charging power is involved simultaneously in this paper. The randomness of EV charging power is formulated based on the TOU (time of use) electricity tariff first. Then another scenario is addressed in which the EV charging power is dispatched to obtain the minimum equivalent load with quadratic programming. 3PEM PLF is formulated, considering weather conditions. At last the proposed method is tested by PG&E 69 [23] (American Pacific Gas and Electric Company) bus distribution system. The PV generation connection position is optimized. The relationships between the voltage profile and the PV generation, EV charging power, load power are analyzed based on simulation results.

Randomness of the PV generation power, EV charging power

Randomness of PV output

Daily sunshine hour S refers to the time the radiation get to the ground perpendicularly on the intensity of more than or equal to 120 W/m^2. Once the daily sunshine hour S is obtained from meteorological data, the daily radiation H can be expressed as Angtrom–Prescott Eq. (1) [24]

$$H = H_L\left(0.248 + 0.752\frac{S}{S_L}\right) \tag{1}$$

where S_L is day length hours which can be computed with Eq. (2). H_L is the solar radiation passed through the atmosphere.

$$S_L = (2/15)W_S \tag{2}$$

$$H_L = \tau \times H_0 \tag{3}$$

where W_S is hour angle computed in Eq. (4). H_0 is the sunshine radiation outside the atmosphere. τ is the transmittance coefficient of the atmosphere, τ is about 0.2–0.8 according to the atmosphere conditions such as water vapor and dust et al. The probability density function (PDF) of τ is as Eq. (6) [25].

$$W_S = \cos^{-1}(-\tan\Phi \times \tan\delta) \tag{4}$$

$$H_0 = (1/\pi) \times G_{SC} \times E_0 \times (\cos\Phi \times \cos\delta \times \sin W_S + (\pi/180) \times \sin\Phi \times \sin\delta \times W_S) \tag{5}$$

$$f(\tau) = c\frac{\tau_{max} - \tau}{\tau_{max}}e^{\lambda\tau} \tag{6}$$

where Φ is the latitude. δ is the solar declination. G_{SC} = 1.367 kW/m^2 is the solar constant which is the solar radiation before it enters the earth's atmosphere. E_0 is the adjusted factor of earth orbit eccentricity. τ_{max} is the max transmittance coefficient, c, λ is constant decided by max and mean transmittance coefficient.

$$\delta = 0.006918 - 0.399912\cos\Gamma + 0.070257\sin\Gamma - 0.006758 \times \cos 2\Gamma + 0.000907\sin 2\Gamma - 0.002697\cos 3\Gamma + 0.00148\sin 3\Gamma \tag{7}$$

$$E_0 = 1.00011 + 0.034221\cos\Gamma + 0.00128\sin\Gamma + 0.000719 \times \cos 2\Gamma + 0.000077\sin 2\Gamma \tag{8}$$

$$c = \frac{\lambda^2\tau_{max}}{e^{\lambda\tau_{max}} - 1 - \lambda\tau_{max}} \tag{9}$$

$$\lambda = \frac{2\gamma - 17.519e^{(-1.3118\gamma)} - 1062e^{(-5.0426\gamma)}}{\tau_{max}} \tag{10}$$

$$\gamma = \frac{\tau_{max}}{\tau_{max} - \tau_{mean}} \tag{11}$$

where Γ is the year angle. $\Gamma = 2\pi(l-1)/L$, l is day number, for example, the day number of January 1 is 1, in leap year, L = 366, and non-leap year, L = 365. τ_{mean} is the mean transmittance coefficient.

When the total daily radiation H is known, the ratio of radiation in each hour to the total radiation from sunrise to sunset can be calculated by Eqs (12) and (13) [26]:

$$R(t) = \frac{1}{\sqrt{2\pi}\sigma_R}e^{\left[-\frac{(t-12)^2}{2\sigma_R^2}\right]} \tag{12}$$

$$\sigma_R = 0.461 + 0.192S_L \tag{13}$$

where $R(t)$ is a cut-off normal distribution function. Mean of the normal distribution is at the solar noon and σ_R is standard deviation. t is from sunrise hour to sunset hour. The radiation of each hour is $H(t) = R(t)H$, with Eq. (14) $H(t)$ it is discounted to the peak power hour $D(t)$. Peak sun hours is the duration when air mass is 1.5, temperature is 25 °C, radiation intensity is 1000 W/m^2, the unit of $R(t)$ is hour.

$$D(t) = H(t) \times 0.0116 \tag{14}$$

where 0.0116 is discount constant. Energy output (kW h) of PV at the tth hour is [27]:

$$W_{PV}(t) = P_{PV} \times \eta \times D(t) \times 10^{-3} \tag{15}$$

where P_{PV} is the installation peak power of PV cell modules, its unit is W. η is the efficiency of the installed PV cell modules. Therefore, the average output power of PV cell at the tth hour is $P_{PV}(t) = P_{PV} \times \eta \times D(t) \times 10^{-3}/1$(kW), here, 1 means one hour. It is can be obtained that $P_{PV}(t) = P_{PV} \times \eta \times R(t)\tau H_0\left(a + b\frac{S}{S_L}\right) \times 0.0116 \times 10^{-3}$ kW from Eqs. (1)–(15). For $P_{PV}(t)$ is linear function of τ, $P_{PV}(t)$ obeys the same probability density function as τ. Then the jth central moments or origin moments of PV generation can then be obtained (Appendix).

Randomness of EV charging

The plug-in time is always random though dispatch method is intervened in EV charging procedure. Since in our work the charging point is connected to the LV (low voltage) network, so slow charging mode is adapted while the fast charging mode is often adapted in charging stations which is connected to the MV (middle voltage) network. Slow charging mode which is often called 0.2C charging mode. This means 5 h is necessary to reach the full storage capacity when the battery is totally empty