Electric Power Systems Research 157 (2018) 126–133

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Probabilistic modeling of electric vehicle charging pattern in a residential distribution network

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ARTICLE INFO

Article history:
Received 5 July 2016
Received in revised form
13 November 2017
Accepted 6 December 2017

Keywords:
Electric vehicles
Distribution system

ABSTRACT

It has been recognized that an increased penetration of electric vehicles (EVs) may potentially alter load profile in a distribution network. Charging pattern of EVs and its corresponding electrical load pattern may be assessed and quantified by using either a deterministic method or stochastic approach. However, deterministic method does not account for stochastic nature of EV users which affects the load pattern and of stochastic nature of grid condition. Thus, a stochastic method is applied to develop a probabilistic model of EVs charging pattern that takes into account various factors such as vehicle class, battery capacity, state of charge (SOC), driving habit/need, i.e. involving trip type and purpose, plug-in time, mileage, recharging frequency per day, charging power rate and dynamic EV charging price under controlled and uncontrolled charging schemes. The probabilistic model gives EV charging pattern over a period of day for different months to represent the load pattern during different seasons of a year. The presented model gives a rigorous estimation of EV charging load pattern in a distribution network which is considered important for network operators.

1. Introduction

Assessment of additional loading profile of expected overwhelming EVs charging in a distribution network could be carried out using either deterministic method or stochastic modeling of EVs load [1,2]. As a fact of matter, it's complicated to quantify a number of EV charging events per day and the associated load and impact on the grid through a deterministic approach because it involves multiple factors involving complete mobility pattern of an EV driver/owner. Rather, an EV charging pattern and its corresponding power consumption may either be quantified based on daily driving pattern/individual's activity schedule. Where, EV charging pattern means the pattern of EV charging and its corresponding electrical load curve pattern. It describes that how many EVs are required to be recharged (and are plugged-in) during different intervals of a day throughout the varying seasons of a year. Charging pattern of EVs and its corresponding electrical load pattern may be assessed by using either a deterministic method or stochastic approach. However, deterministic method does not account for stochastic nature of EV users which affects the load pattern. Thus, a probabilistic model of EVs charging pattern is developed that takes into account various factors including: electric vehicle class, battery capacity, state of charge (SOC), driving habit/need, i.e. involving trip type and purpose, plug-in time, mileage, recharging frequency per day, charging power rate and dynamic EV charging price under controlled and uncontrolled charging schemes. Thus, there is need to develop a probabilistic model of EV charging in the system to estimate an expected load data that may be used by utilities to upgrade their infrastructure for supporting large penetration of EVs [1]. For utility companies, EVs are to be preferably recharged during night when residential power demand is a bit less whereas EV drivers want to recharge their car as soon as they finish a trip and charging time is conveniently available. In literature, mostly authors modeled EV charging load based on some reasonable assumption while ignoring a few important aspects. For instance, in [3], authors assume a fixed percentage of EVs and in [4] all EVs are assigned a certain distance traveled per day. A rigid EV charging schedule is assumed in [5,6]. Authors in [7,8] assume a certain mileage and corresponding fixed amount of power consumption by each EV. Papers [9,10] consider a predefined probability distribution curve to estimate a covered mileage and associated power consumption. Moreover, [13] take into account various factors including distance driven, car velocity, trip duration, trip purpose, a deferred charging event i.e. when an EV needs to be recharged but its driver delays the

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https://doi.org/10.1016/j.epsr.2017.12.005

recharging due to his/her own preference or convenience. References [2,14] illustrate the starting time by sampling the given data. Nonetheless, these approaches come with limitations of defining the right charging moment that whether it's taken when an EV is recharged after performing its last trip of the day or it occurs right after first commuting trip. Most of these factors are considered as a parameters of controlled and or optimized charging schemes with different objectives such as reducing charging cost, stress on the grid and etc.

This paper is focused on devising a probabilistic model to determine an EV charging pattern in a residential distribution network that is developed while considering all the relevant factors, the stochastic modeling approach is explained in Section 2 that also includes profile of departure and travel time. An EV activity pattern model is given in Section 3 and modeling of EVs state transition probability is explained in Section 4. Then, estimation of charging profile and case study are described in Sections 4.1 and 5. The results are presented in Section 6 and the paper is concluded in Section 8.

2. Stochastic modeling of EV charging

This model is aimed at estimating an EV charging profile based on activity pattern of residents. Its output describes EV charging pattern over 24 h of a day and it in order to figure out an appropriate estimation of load pattern and its impact on distribution network, it is important to take into account most possible activities of EV users. Following factors are considered and need to be defined for stochastic modeling to come up with a probabilistic charging pattern of all EVs in the system at a particular instant of time: EV penetration level in the study network, class of EVs (car, van), EV battery capacity, state of charge (SOC) of battery at time t, EV driving habits, type of trip in view of trip purpose in terms of schooling, commuting, holiday trip, mileage, vehicle battery capacity, charging need and charging time (plug-in moment), recharging frequency per day, usage diversity and dynamic charging price factor under controlled and uncontrolled charging in accordance with peak and off-peak hours, i.e. these are categorized based on grid loading conditions and corresponding variable electricity price. The definition of EV penetration level considered in this paper is the ratio of number of electric vehicles to the total number of vehicles in a given study area. In this regard, number of EVs is determined based on the statistics issued from German Federal Statistical Office [15] and these numbers are used to estimate the number of EVs that may be added to the system at different penetration levels. However, a minimum fleet of 104 EVs is taken in this model in a given residential area (as per Ref. [15]) which are then increased with increasing penetration level. The presented work proposes probabilistic model of EV charging pattern over a period of 24 h through stochastic modeling of the corresponding features, as mentioned above. In order to be as detailed as possible, the paper considers trip type based uncontrolled and controlled EV charging schemes for weekday, weekend during months m_1, m_2 and m_3 that include March to May, June to August and December to March that represent spring, summer and winter seasons, respectively. Varying EV penetration levels are considered to obtain variety of results for carrying out rigorous results. Furthermore, effect of considering uncontrolled and controlled EV charging schemes along with stochastic features, described above, appears to be salient in determining the EV charging pattern. The probabilistic model gives EV charging pattern over a period of day for different months to represent the EV charging load pattern during different seasons of a year.

The charging need is reflected in terms of amount of electrical energy consumed by driving an EV or total energy transferred to EV battery when plugged-in for recharging. In the stochastic modeling, plug-in time and charging moment of EV charging are considered important, as it may reflect an instant increase in load when an EV is plugged-in. It is worth-noting that number of charging event may not be simply computed based on number of EVs in a distribution network zone rather it depends on activity pattern of an individual and the related iterations.

2.1. Departure and travel time framework

Profile of departures and travel (DTP) time is represented as a binary pattern. In order to formulate the pattern, two states are defined including available and unavailable. The first one corresponds to car being recharged; unavailable state means, the charging is not being taken place. Let T be time of a full day, the departure time is represented as S_i and the distance traveled is μ_i i.e. an EV starts travel at S_i and remains in travel for period μ_i. The statistics of departure and travel times are taken from [11,12]. Estimation of maximum likelihood of a departure and travel times for an individual, in a period of day, is formulated based on the statistical date given in Refs. [13,14,16]. Considering $\gamma(t) \in \{0, 1\}$ and $S_0 \in \{1, 2, \ldots, T\}$ as two variables that represent a state at time t and the latest departure time respectively.

Given: $\gamma(t)$ and S_0 to find: $(S_1, \mu_1), \ldots, (S_k, \mu_k)$, and maximizing:

$$J = (S_1, \mu_1) = \left(\tilde{S_1}, \tilde{\mu_1}\right), \ldots, (S_k, \mu_k) = \left(\tilde{S_k}, \tilde{\mu_k}\right) \tag{1}$$

$$\forall_i \in \left\{1, 2, \ldots, k\right\} (t \le S_i \le t + T, 1 \le \mu_i \le T) \tag{2}$$

$$\forall_j \in \left\{1, 2, \ldots, k\right\} \left\{ \left(S_i, S_j + \mu_i\right) n \left(S_i, S_j + \mu_i\right) = \phi \right\} \tag{3}$$

where, $k \in \{1, 2, \ldots, T\}$ represents number for departures for an EV, S_i and μ_i are random variables and $\forall$ is a universal quantifier. Objective of the function defined in Eq. (1) is to represent a joint probability as a combination of two states S_i and S_j. Eq. (2) implies that only current departure time is considered in a period of a day where travel time of an EV must fall within T. Eq. (3) means that there should not be an overlapping/repetition of traveling periods (i.e. one travel time is calculated only once), thus the duration of travel must be predicted for a day [17].

Incorporating Markov model for estimation of DTP the above equations can be written as, let *SDTP* be the statistics related to DTP taken from [18]. This sections does contain the complete mathematical model due to available space limitation. In view of left-to-right Markov model, the objective function may be written as in Eq. (4), and its maximum likelihood function is given in Eq. (5) [19,20].

$$\begin{aligned} J &= \pi_{x_t} a_{x_{t+1}x_t}(t) \; a_{x_{t+2}x_{t+1}}(t+1) \cdots \\ &\quad a_{x_{t+T}x_{t+T-1}}(t+T-1) \epsilon_{x_{t+T}}(t+T) \end{aligned} \tag{4}$$

$$\begin{aligned} J^* &= \max \left[\pi_{x_t} a_{x_{t+1}x_t}(t) \quad a_{x_{t+2}x_{t+1}}(t+1) \cdots \right] \\ &\quad \left[a_{x_{t+T}x_{t+T-1}}(t+T-1) \epsilon_{x+T}(t+T)\right] \end{aligned} \tag{5}$$

Having decomposed the maximizing process using Markov property and introducing some variables to obtain recursive solution, as given in Eq. (7), with $\tau = t$ and $\tau \ge t+1$, Eq. (6) is obtained and an optimal state after $t+T$ is given in Eq. (9):

$$\delta_\tau(x_\tau) = \begin{cases} \pi_{x_\tau} \\ \max \left[\delta_{\tau-1}(x_\tau - 1) a_{x_\tau x_{\tau-1}}(\tau - 1)\right] \end{cases} \tag{6}$$

$$\psi_\tau(x_\tau) = \underset{x_{t-1}}{arg \; \max} \; \left[\delta_{\tau-1}(x_{\tau-1}) a_{x_t} x_{\tau-1}(\tau - 1)\right] \tag{7}$$