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Non-Gaussian multivariate modeling of plug-in electric vehicles load demand

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ABSTRACT

This paper proposes an organized stochastic methodology to model the power demand of plug-in electric vehicles (PEVs) which can be embedded into probabilistic distribution system planning. Time schedules as well as traveling and refueling information of a set of commuter vehicles in Tehran are utilized as the input dataset. In order to generate the required synthetic data, the correlation structure of the aforesaid random variables is taken into account using a multivariate student's *t* function. Afterwards, a Monte Carlo based stochastic simulation is provided to extract the initial state-of-charge of batteries. Further, a non-Gaussian probabilistic decision making algorithm is developed that accurately infers whether the PEVs charging should take place every day or not. Then, through presenting a state transition model to describe the charging profile of a PEV battery, hourly demand distributions of the PEVs are derived. The obtained distributions can be used to generate the random samples required in probabilistic planning problems. Eventually, the extracted distributions are employed to estimate demand profile of a fleet that can be efficiently utilized in various applications.

Introduction

Recently, a considerable attention has been paid to plug-in electric vehicles (PEVs) as one of the promising and effective means to create new opportunities in energy security and environmental issues. However, this emerging vehicular load, especially in localities with high levels of PEV adoption, results in new customer demand patterns that may lead to adverse effects on the quality and stability of the grid [1–4]. Due to the lack of historical data about the behaviors of PEVs, estimating the power demand of these vehicles may be considered as one of the critical challenges in various distribution system applications such as network planning, probabilistic load flow, demand side managements and sitting/sizing issues [5,6].

Majority of the previous PEV modeling studies have used deterministic methods to derive the demand curve of the PEVs [7–10]. However, applying the deterministic methods, due to the related uncertainties, can be problematic in the practical implementations and therefore, it is essential to employ stochastic and probabilistic modeling approaches [2,11,12]. For instance, the work described in [13] assumed that the PEVs demand profile as well as the number of the connected PEVs to grid follow univariate Normal PDFs. In [3,6,14], Normal distribution functions were created to assign the charging start time of PEVs. Also, the SOC_{init} of PEVs was determined by a Normal PDF.

As a misleading and highly questionable assumption, the stochastic factors related to PEVs were generally supposed to be independent and without any correlation. A very limited number of studies attempt to take this issue into account. For instance, in [15] a normal copula was applied to model the uncertainties. However, the technique can be arguable due to some real life issues such as the tail dependence among the involved variables (Section 'Case study and discussions'). In addition, the occurrence of daily charging of PEVs was decided according to a deterministic criterion.

This paper proposes an algorithm based on non-Gaussian multivariate stochastic models in order to extract the hourly aggregated load demand of PEVs. The methodology involves a probabilistic decision making process extracted by employing the realistic data to infer accurately whether the PEVs charging should take place every day or not. Moreover, in order to describe the charging process of a PEV battery, a state transition model is presented where the powers on which the battery charging is fulfilled are expressed as the states. Time schedules as well as traveling and refueling information of a set of commuter ICE vehicles in Tehran are utilized as the input dataset. In order to generate the required synthetic data, these RVs are, at first, modeled as marginal

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Nomenclature

$BATT_{CAP}$	battery capacity (kW h)
$C(.)$	Copula function
CDF	cumulative distribution function
$c(.)$	Copula density function
E(.)	expected value of an RV
EFF_{Chg}	efficiency coefficient of a battery charger (%)
EFF_{DRV}	efficiency coefficient of PEVs during driving (km/kWh)
EFF_{ICE}	efficiency coefficient of ICE vehicles during driving (km/Liter)
$F(.)$	univariate CDF
$F^{-1}(.)$	inverse of univariate CDF
f	subscript index for final state of a battery
$f(.)$	univariate PDF
Gev	generalized extreme value
$H(.)$	multivariate CDF
h	subscript index for daily hours
$h(.)$	multivariate PDF
ICE	internal combustion engine
m	subscript index for Monte Carlo loop
n	subscript index for simulated vehicles
PDF	probability density function
p	subscript index for RVs
P^{BATT}_{Chg}	battery charging power (W)
P^{BATT}_{ChgMax}	power rating of a battery charger (W)
$\mathbf{R}$	correlation matrix
$\Re$	set of real numbers
RV	random variable
SOC	state-of-charge
SOC^{e}	estimated state-of-charge of batteries
SOC_{init}	initial state-of-charge of a PEV battery (%)
T_{Avail}	available time to charge a PEV battery
T_{Full}	the necessary time for a battery to be completely charged
$TANK_{CAP}$	capacity of fuel tank of ICE vehicles (Liter)
$\mathbf{TRAV}^{e}$	set of estimated length of the next day traveling of ICE vehicles
tp	subscript index for plugging time
$\mathbf{u}$	vector of uniform random variable
u	uniform random variable
$\mathbf{x}$	vector of random variables
x	random variable
$\boldsymbol{\mu}$	vector of means
$\boldsymbol{\rho}$	linear correlation matrix
υ	degree of freedom

distributions. Unlike most of the literature that, for the sake of simplicity, used the Normal PDF, this paper employs appropriate non-Gaussian PDFs to fit to the RVs. Then, to avoid unreliable and inconsistent estimates, the correlation structure is modeled using a student's *t* copula distribution. Afterwards, a Monte Carlo based stochastic modeling algorithm with two scenarios to extract the SOC_{init} of PEV batteries is thoroughly explained. By applying the algorithm, hourly load distribution functions of the PEVs is derived that efficiently can be used in probabilistic planning problems. Eventually, the provided curves are thoroughly discussed in order to elaborate their characteristics.

The remainder of this paper is organized as follows. Section 'The modeling methodology' elaborates the proposed modeling methodology. The notion of employed multivariate modeling algorithm as well as the method to generate synthetic data is explained in Section 'Multivariate modeling'. Then, the simulation results are discussed in Section 'Case study and discussions'. Finally, the paper is concluded in Section 'Conclusions'.

The modeling methodology

Battery initial SOC

Extraction of the battery SOC_{init} is done with assuming following scenario cases:

Case 1: As the worst case scenario, SOC_{init} can be supposed to be a constant. This constant is determined according to the depth-of-discharge (DOD) of the PHEVs as follows:

$$SOC_{initn} = 100 - DOD \tag{1}$$

However, it is suggested to alter (1) by using randomly generated positive numbers through employing an Exponential PDF as below:

$$\begin{cases} SOC_{initn} = 100 - DOD + Rand(f_{\exp}(x)) \\ f_{\exp}(x) = \frac{1}{\mu_{\exp}} e^{-\frac{x}{\mu_{\exp}}} \end{cases} \tag{2}$$

Case 2: The SOC_{init} is determined based on the daily traveled distances. Regarding the fact that T_{Avail} in home charging is usually bigger than T_{Full}, it is rational to assume that the battery SOC at the departure time is 100%. Hence, the SOC_{init} of a PEV can be derived as:

$$SOC_{initn} = 100 - \frac{TRAV_n}{EFF_{DRV} \times BATT_{CAP}} \times 100 \tag{3}$$

where EFF_{DRV} is dependent on the driving patterns and traffic conditions as well as power electronics-based driver efficiency of the electric motors.

PEV charging occurrence

In reality, refueling ICE vehicles is highly dependent on the state-of-fuel at the refueling time as well as the anticipated distance of the upcoming journeys. Decision making on occurrence of the battery charging can be a challenging issue due to its direct impacts on the derivation of PEV demand profile [16]. It can be simply supposed that charging process of the PEVs should be fulfilled every day after arriving; However, following abovementioned refueling pattern of the ICE vehicles, occurrence of a PEV charging should be decided regarding its SOC_{init} as well as estimated length of the next day traveling denoted by $TRAV^{e}$.

In this paper, with the aim of providing an accurate and precise methodology, a non-Gaussian probabilistic decision-making (PDM) process is planned. The devised PDM process employs the $\mathbf{SOC}_{init}$ and $\mathbf{TRAV}^{e}$ samples to generate a bivariate PDF to infer whether the PEV charging should take place or not. In order to prepare the mentioned samples, a set of data related to the state-of-fuel of the ICE vehicles at the refueling time ($\mathbf{SOF}_{init}$) as well as the anticipated distance of the upcoming journeys should be gathered. Then, it is necessary to transform the $\mathbf{SOF}_{init}$ to the equivalent SOC data denoted by $\mathbf{SOC}^{e}_{init}$. In this regard, it is suggested to estimate, at first, the distance that can be traveled using a SOF_{init} and then, taking into account the capacity of the employed battery, to extract the SOC^{e}_{init} that is required to travel the same distance by a PEV. The SOC^{e}_{init} of each PEV can be calculated as:

$$SOC^{e}_{initg} = \frac{SOF_{initg} \times TANK_{CAPg} \times EFF_{ICEg}}{EFF_{DRV} \times BATT_{CAP}} \tag{4}$$