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Markov Chain Monte Carlo simulation of electric vehicle use for network integration studies

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ABSTRACT

As the penetration of electric vehicles (EVs) increases, their patterns of use need to be well understood for future system planning and operating purposes. Using high resolution data, accurate driving patterns were generated by a Markov Chain Monte Carlo (MCMC) simulation. The simulated driving patterns were then used to undertake an uncertainty analysis on the network impact due to EV charging. Case studies of workplace and domestic uncontrolled charging are investigated. A 99% confidence interval is adopted to represent the associated uncertainty on the following grid operational metrics: network voltage profile and line thermal performance. In the home charging example, the impact of EVs on the network is compared for weekday and weekend cases under different EV penetration levels.

1. Introduction

As the EV penetration level increases, accurate prediction of the associated electricity consumption is required for network side planning, in particular, network asset investment, [1]. The associated uncertainty in load is also of essential importance to the network normal operation since it allows the network operator to leave sufficient margins during the planning stage as well as in operation. The large sample size that is required for the uncertainty investigation justifies the construction of a suitable model for detailed simulation of vehicle use patterns. To be useful, the EV charge requirements and their timing must reflect actual driving practice both in terms of journey length (duration) and start and finish times, and also include the main locations at which charging can be undertaken.

Stochastic techniques lend themselves to vehicle use modelling due to the random nature of driving patterns. Monte Carlo simulation, as a stochastic modelling approach, is a popular choice, such as [2–6].

Detailed Markov Chain Monte Carlo (MCMC) simulation was used to generate weekly EV patterns in [2] with half hourly resolution. The initial states were defined assuming a Gaussian distribution for EV characterisation, and the subsequent instances were produced based on the Markov Chain transition probabilities using Monte Carlo simulation. One infeasible assumption in this particular simulation was that the driving period per journey was fixed to be 30 min, which is due to the lack of self-transition status of driving, and this limits the generation of continuous vehicle driving states.

Iversen et al. also employed Markov Chain models for describing vehicle diurnal driving patterns in [3], including the discrete time Markov model, where the size of the state transition matrix was proportional to the time resolution and vehicle states considered, the continuous time Markov model, where possible parameter reductions can be obtained compared with the discrete model, and the hidden Markov model, which allowed for modelling states that are not directly observed in the data by introducing a new state to the original Markov model. The associated application however was constrained to the two vehicle status of 'driving' and 'not driving' without any charging locations allocated.

Another example of Monte Carlo simulation is presented in [4] where three key variables, consisting of the time of vehicles' arrival and departure time at and from charging locations and the travelled distance in between, were selected from a transportation database for vehicle motion generation. Since the variables were statistically dependent, a copula function was employed to join the univariate distribution functions to build the joint multivariate distribution function for both a single and double journeys, which was then used for the Monte Carlo simulation to model vehicle use patterns.

A Gaussian distribution, non-uniform distribution and conditional Gaussian distribution was assigned in [7] for simulating the arrival time, charging time and departure time, respectively. Similar distributions have also been assumed for EVs' arrival and departure in [8] and [9] respectively. In reality, however, such predefined distributions are sometime unsuitable for vehicle pattern simulation. For example, [10]

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sampled from a Gaussian distribution function to synthetize the travelled distance, which according to [4] was correlated with and therefore should be determined by the departure time of the commuter.

Ref. [1] also proposes a statistical modelling approach to generate daily driving patterns, where the temporal distribution of departure and arrival times and their correlation were modelled first, and the synthetic driving cycles associated with the driving distance distribution were then constructed. The acceleration related variables used for synthetic driving pattern construction in [1] are however unavailable in most of the transportation data, which would limit the application of the method.

A multi-agent system with percolation approach is presented in [11] for simulating EVs' driving patterns, where mobile and static agents are employed and the percolation methodology is used to identify probable locations of EV charging activities.

It is important that the synthetized vehicle patterns are verified against the original vehicle records, but so far not many publications have been found that have undertaken this. The closest are the work presented in [5], where the seasonal charging loads that were generated from various stochastic models were compared with those from the original GPS based vehicle use patterns, and [1], where simulated arrival time distribution is verified against the original real-life measurement. This present paper makes a contribution by providing a detail verification of vehicle characterisation as well as different charging location scenarios.

Following on from the development of synthetic EV driving patterns, these models have been used to analyse the impact of EV charging on the distribution network, such as [6], which estimated the thermal effect of EV charging on transformer aging, and [12], in which the peak load, total loss and voltage violation of the system due to the EV charging load under different year scenarios were investigated.

It is understood that the stochastic nature of EV motion would lead to uncertainties in the EV demand curve and therefore network operational metrics. The uncertainty of EV load due to one million EVs under the scenario of uncontrolled domestic charging was analysed in [4], but only on a nationally aggregated demand scale. This present paper calculates the uncertainties of the EV demand and associated network metrics due to EV patterns using the MCMC simulation. Such uncertainty analyses provide precious information for the network operators and also help with system planning. The other strengths of this work are the high time resolution of ten minutes and the detailed and verified representation of vehicle use.

National transportation statistics such as National Household Travel Survey [13] and Mobility Research Netherlands [14] have been in support of EV investigations in [6] and [4] respectively. The present work utilizes the 2000 UK Time of Use Survey (TUS) data, [17], because of its high time resolution and in order to be consistent with the domestic electricity consumption model [15] which was developed based on the same set of data and will be employed here to generate the domestic base load, house by house.

The work presented in this paper utilizes MCMC simulation to generate synthetic EV use patterns based on vehicle movement characterisation, in this case from the TUS data. By using MCMC simulation, the impact of the uncertainty in EV load on the power system is investigated at a distribution network level.

1.1. Contribution of this work

The fore-mentioned works have been summarised in Table 1 in terms of 6 model features that the presented work possesses, from which it can be seen that the contributions of this work are fine data resolution, which allows detailed and accurate vehicle movement modelling, verification of vehicle driving patterns, which guarantees the simulation accuracy, and uncertainty analysis of network impact, which is important for grid planning and operation.

The MCMC simulation presented in [16] was rather provisional in the sense that model results were not subject to verification and uncertainty analysis for practical network assessment was not undertaken. The present paper includes both these important elements.

Table 1
Summary of relevant literature works.

	A	B	C	D	E	F
[1]	✓	✓	✓	✓	—	—
[2]	✗	✓	✗	✗	✓	✗
[3]	✓	✗	✓	✓	✗	✗
[4]	✗	✓	✓	✗	✗	✗
[5]	✗	✓	✓	✓	✗	✗
[6]	✗	—	—	—	✓	✗
[7]	✗	✓	✗	—	✗	—
[10]	✗	✓	✗	✗	—	—
[12]	✗	✓	✗	—	✓	✗
[16]	✓	✓	✓	✗	✓	✗
This work	✓	✓	✓	✓	✓	✓

A: Fine data resolution (less or equal to 10 min per step).
B: Vehicle status definition.
C: Vehicle movement simulation.
D: Vehicle use pattern verification.
E: Detailed network impact analyses considering charging location.
F: Uncertainty analysis of detailed network impact.
✓: model feature is included in a suitable manner.
✗: model feature not included.
—: not relevant.

The work in [2] was simplified by assigning a fixed driving period of 30 min per journey in the Markov Chain transition model construction, which has a completely different driving period distribution from the TUS data, as will be presented later in this paper. The vehicle movement modelling using this assumption in [2] would therefore be inaccurate. This present work contributes to improve the Markov Chain model by adding a self-transition of driving to the state transition diagram which was absent in the work of [2], and the finer data resolution defined by the TUS data used here is capable of capturing more accurate vehicle movement.

2. Time of use survey (TUS) data

The UK 2000 time of use survey (TUS) [17], was carried out on domestic activities for both weekdays and weekends including the use of privately owned vehicles. Each survey was on a 24-h basis with 10-min resolution, starting at 4.00 am and ending at 3.50 am the next day, since activities reached a minimum around this time of day [17]. The vehicle driving related survey diaries were chosen for the analyses in this work, and the vehicle status for such diaries were classified into four distinct states: namely 'driving'; 'parking at home'; 'parking at workplace'; and 'parking at commercial areas'. The vehicles' departure and arrival activities and individual journey time could then be subsequently obtained for the selected database. It should be noted that a further process of removing any diaries with a daily journey longer than 180 min was undertaken to reflect the feasible electric range of EVs in accord with the EV specification in Section 4. The number of diaries from the processed TUS data is 1476 and 2642 for the weekday and weekend data, respectively.

The statistical characteristics of the selected TUS data that involve vehicle driving are illustrated in Figs. 1–4 for both the weekday and weekend case. In both cases the vehicle activities are configured based on the assumption of a periodically stationary daily cycle from 4 am to 3.50 am the next day due to the minimal activities at this period, which is verified by the smooth transition at this time of day as illustrated in Fig. 1. A morning and evening weekday driving peak can be overserved in Fig. 1(a), which can be confirmed as for commuting purpose by referring to the associated arrival and departure activities from Fig. 2(a), where the probability value is obtained by dividing the associated