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Public charging infrastructure in Japan – A stochastic modelling analysis

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ABSTRACT

Electric vehicles (EV) are treated as a breakthrough technology in the automotive market. The novelty of this technology also implicates that the incidence of these vehicles worldwide is still low. An important issue regarding EVs is the existence of proper charging infrastructure as waiting at charging stations due to an inadequate number of chargers can discourage EV owners. However, as the number of EVs and charging stations are low at present, real world experience is not available, so computer simulations are required for the planning of such charging stations.

We developed a stochastic model in this paper that includes driving and charging behaviour of EV owners in Japan. The model is based on Monte Carlo methods and was implemented in MATLAB. We conducted simulations with this model to find out whether the existing infrastructure is adequate for the charging of a large number of EVs. The results indicate that Japan is well prepared for an increase in plug-in vehicles (PHEVs) in the near future: currently the country has 6 fast chargers for 100 electric cars and for this ratio - on average -, waiting probability at DC (direct current) fast chargers ranges lower than 5%, which is an acceptable value for EV owners. If, however, the ratio decreases, waiting probability increases exponentially.

1. Introduction

Japan has one of the most progressive industries in terms of alternative drive vehicles [1]. The Electric Vehicle Index published by McKinsey every half year continuously ranks Japan top. Furthermore, Japanese OEMs (Original Equipment Manufacturer) hold the most sold EV (Nissan Leaf), PHEV (Mitsubishi Outlander), hybrid vehicle (Toyota Prius) and fuel cell vehicle (Toyota Mirai) [2].

In the current commercial phase, Japan was the country of the first launch of a commercial EV: Mitsubishi launched its 'i-MieV' in 2009. Since that launch, around 120,000 PHEVs (PHEV and EV) have been sold in Japan and around 80% of them are equipped with fast charging abilities [5]. Next to a strong industry, Japan has continuously invested in charging infrastructure for pure EVs and PHEVs. The country-wide fast charging standard CHAdeMO is also used in most fast charging stations throughout the world (around 6000 CHAdeMO fast chargers have been installed in Japan, 2000 in Europe and 1500 in the USA [3,4]). This means a ratio of 5.9 fast chargers per 100 fast charging compatible vehicles in Japan [4].

The literature dealing with charging station and individual charger location planning is vast, stochastic models are widely used for this purpose. A similar approach to our planning procedure can be found in [7], where the authors attempt to address both the system-level scheduling problem and the individual control problem, requiring only distributed information about EVs and their charging at service stations. They utilize the M/M/c queuing process. Authors of [8] describe a tool based on Monte Carlo techniques to identify load scenarios associated with electric car charging. Our paper uses a similar procedure, but with a more accurate stochastic algorithm. The authors of [9] propose a model for PHEV utilization to determine charging load profiles based on driving patterns due to the type of trip and corresponding charging need, also based on Markov chains. [10] presents a methodology to estimate grid availability for cars with the use of a non-homogeneous semi-Markov process. In [11] the authors propose a model for generating PHEV home charging patterns by combining PHEV usage with other residential consumption. PHEV usage is modelled with Markov chains. Our paper complements these models with detailed vehicle motion simulations, making it possible to monitor EVs' SOC (State of Charge) development during motion and charging. It also takes into consideration the nonlinear charging characteristics of batteries under fast charging and the diversity of car usage.

The paper continues as follows: In Section 2, we describe the modelling assumptions, the initial data and the distribution fitting procedures: we fit distribution functions to datasets describing

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vehicle travel time and distance, energy consumption and initial SOC level, charging time at slow and fast chargers. Detailed analysis is given for each fitting step. In Section 3, we present the main algorithm of the model: this is a down-scaled model based on Monte Carlo simulations, including one hundred EVs and six public fast chargers. In Section 5, we present and discuss simulation results obtained with the proposed model. Section 4 describes the limits of the model while Section 6 concludes our paper.

2. Modelling assumptions

The proposed stochastic model utilizes different states to define whether the vehicle is parking, moving, charging or waiting at a charger. The transition probabilities between different states are based on the pre-processing of data from [6,12,13].

The e-Denpi report by iid [6], a market research organization that measures fuel consumption of cars, measured the consumption of 43 Nissan Leafs in Japan over the course of 3550 trips. All data used here was provided from the executive summary available in English and Japanese.

Results from the EV Project [12] were used in the case when data was not available from [6]. The EV Project continuously records driving and charging behaviour of 4261 Nissan Leaf drivers from 17 different regions over the course of 1,135,053 trips. The data was taken from the latest publicly available report, the Q2 2013 Report.

The following data were taken from the aforementioned sources:

- number of vehicles driving,
- trip distance,
- ratio of fast vs. slow charging,
- duration of charge,
- distance to closest fast charger,
- average driving speed,
- energy consumption of vehicles.

The data inputs are converted into distributions from which the model randomly draws during simulations. Index l indicates the number of the given car and index k is the discrete time index (in our case the sampling interval - i.e. time step - was 5 min).

2.1. Vehicle usage

Car usage statistics were extracted from [13]. The statistics showing vehicle usage can be seen in Fig. 1: grey lines are individual days' data, while the orange curve is the average of this dataset. We used this average in our model. This is a limitation, as the modelling could have been extended into a stochastic driving behaviour, i.e. taking individual driving scenarios into account and constructing a distribution function that characterizes the number of moving cars at a given time instant. Due to lack of proper data this approach was dismissed in the current paper.

The data was approximated using three separate Gaussian distributions and implemented in MATLAB (Fig. 2). By comparing Figs. 1 and 2 we can see that the simulated dataset approximates the original one well.

In order to know whether a vehicle is moving at a time step, we define the variable $vs^l[k]$ as follows:

$$vs^l[k] = \begin{cases} 0, & \text{if vehicle } l \text{ is not moving in } k \\ 1, & \text{if vehicle } l \text{ is moving in } k \end{cases} \tag{1}$$

where k is the time step, l is the vehicle number.

The algorithm then compares the currently moving vehicles with the number of vehicles suggested in Fig. 2 and randomly

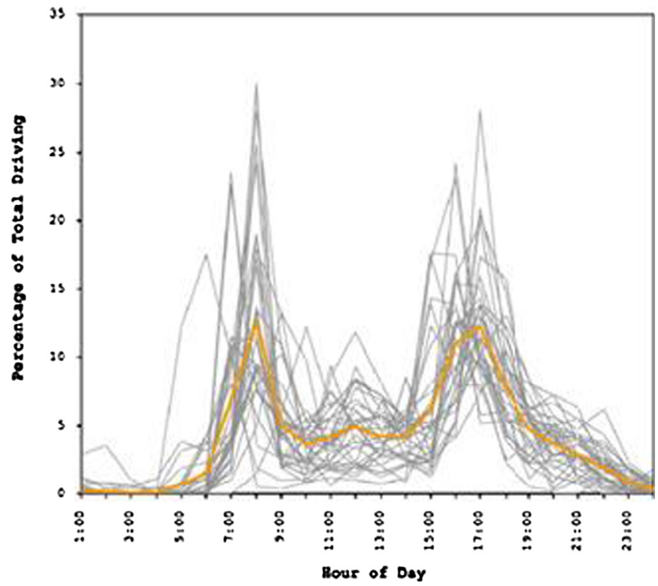

Fig. 1. Number of moving cars during the day [13].

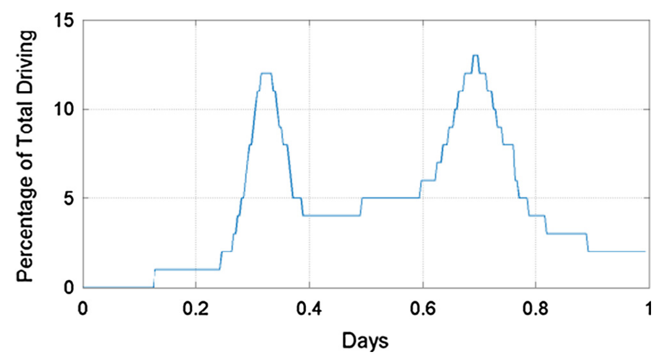

Fig. 2. Number of moving cars simulated in MATLAB, no. of cars: 100.

selects a not moving or charging car to move so that the ratio of moving cars is always in accordance with the number of moving cars required by Fig. 2. If the number of moving cars is equal to or larger than the prescribed value in Fig. 2, no car is added to the driving vehicle pool and the model 'waits' for a car to return.

The vehicles starting to drive are defined for every time step k as follows:

$$l \in NewV[k], \quad vs^l[k-1] = 0 \tag{2}$$

where $NewV[k]$ is the set of cars to start driving in period k.

2.2. Driving distance distributions

We used Monte Carlo simulation to generate driving distance for each vehicle for each trip. For this purpose, distribution functions had to be fitted to data extracted from [6] (Fig. 3 depicts this data). We obtained trip length distribution from a survey made among Nissan Leaf EV owners in Japan.

Refs. [14,15] suggest that the distribution of travelled distances for a single trip follows exponential distribution. The distribution was generated with MATLAB's 'allfitdist' function [16] and can be seen in Figs. 4 and 5. MATLAB outputs the distribution that fits best to the dataset according to the Bayesian information criterion (BIC).