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Predicting Electric Vehicle Charging Demand using Mixed Generalized Extreme Value Models with Panel Effects

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Abstract

In the past 5 years Electric Car use has grown rapidly, almost doubling each year. To provide adequate charging infrastructure it is necessary to model the demand. In this paper we model the distribution of charging demand in the city of Amsterdam using a Cross-Nested Logit Model with socio-demographic statistics of neighborhoods and charging history of vehicles. Models are obtained for three user-types: regular users, electric car-share participants and taxis. Regular users are later split into three subgroups based on their charging behaviour throughout the day: Visitors, Commuters and Residents.

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Keywords: Electric Vehicle ; Charging Demand ; Discrete Choice Model ; Cross-Nested Logit

1. Introduction

Since 2014 the Dutch metropolitan area (with the cities of Amsterdam, Rotterdam, the Hague, and Utrecht) cooperate in analyzing the performance of public charging stations. By end of 2016 a comprehensive and innovative grid has been created of more than 5600 charging points in the city areas, while more than 2 million charging sessions were recorded. In the coming years the municipality of Amsterdam will invest in the further development of charging infrastructure. One of the most prominent questions for municipalities relates to the question where to place new charging points given that location aspects provide a powerful indicator of energy transfer. How can behavioral data about the usage of charging stations for electric vehicles in the municipality of Amsterdam be modeled to deduce the demand of existing locations? How can the estimated model be used to predict the demand of future locations? In this paper we tackle the question of estimating electric vehicle (EV) charging demand on public charging stations at neighborhood level using the nested (NL), cross-nested (CNL) and mixed cross-nested logit models.[1] These models use certain socio-demographic statistics of neighborhoods and charging history to estimate the share of a specific

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neighborhood of the charging demand of the whole city. The nested logit model is a restricted version of the cross-nested logit model. The cross-nested logit model outperforms the nested model and is in turn outperformed by the mixed cross-nested logit model.

2. Literature review

Many articles have been written about optimizing charging infrastructure based on demand, though this demand is often an unknown. Different researchers have dealt with estimating and measuring this in different ways. Dong, Liu and Lin[2] base their model on the multi-day driving data collected from 445 instrumented gasoline vehicles in the Seattle metropolitan area. Tu, Li, Fang, Shaw, Zhou and Chang[3] use taxi GPS data to estimate demand. Liu[4] assesses the power grid impact if 10% of vehicles were EVs. Jung, Chow, Jayakrishnan and Park[5] model taxi service demand as a Poisson process based on an EMME/2 transportation planning model developed at the Korea Transportation Institute (KOTI). Wang, Wang and Lin[6] optimize charging strategies and charging station placements based on a randomly generated EV network. He, Kuo and Wu[7] optimize charging station location in Beijing, using three classic facility location models. EV demand is estimated using 6 socio-demographic attributes deemed important by the literature, which were then ranked by 11 interviewees. Van den Hoed, Helmus, de Vries and Bardok[8] analyze the data of charging behavior in Amsterdam, using the same data we use. We use a statistical model to estimate demand in Amsterdam based on a number of socio-demographic attributes.

3. Methods and data

The logit models are based on the principle of utility maximization, where the choicemaker simply chooses the alternative with the highest utility, the utility U_i of an alternative i is given by $V_i + \epsilon_i = \beta \cdot x_i + \epsilon_i$, where β is a vector of parameters to be estimated, x_i is a vector of properties of alternative i and ϵ_i is a random variable with a standard Gumbel distribution. In the case of the multinomial logit model (MNL), all ϵ are iid. So U_i are independently distributed Gumbel$(V_i, 1)$, which makes $max_{j\neq i} U_j$ distributed Gumbel$(ln(\sum_{j\neq i} e^{V_j}), 1)$. So the probability that $U_i > max_{j\neq i} U_j$ is:

$$P_i = \frac{e^{V_i}}{\sum e^{V_j}} \tag{1}$$

In the nested logit model (NL), there is a partition on the alternatives $\{N_1, ..., N_k\}$ the ϵ_i are independent if they are in different nests, but within the nest the shared cumulative distribution is given by $\exp\left(-\left(\sum_{j\in N_m} e^{-\epsilon_j \mu_m}\right)^{1/\mu_m}\right)$. This leads to probabilities

$$\tilde{V}_m = \frac{1}{\mu_m} \ln\left(\sum_{j\in N_m} e^{V_j \mu_m}\right) \tag{2}$$

$$P(N_m) = \frac{e^{\tilde{V}_m}}{\sum e^{\tilde{V}_n}} \tag{3}$$

$$P(i|N_m) = \frac{1_{i\in N_m} e^{V_i \mu_m}}{\sum_{j\in N_m} e^{V_j \mu_m}} \tag{4}$$

The cross-nested logit (CNL) allows alternatives to lie in multiple nests at the same time with α_{im} denoting the degree of alternative i lying in nest m, with $\sum_m \alpha_{im} = 1$ for all i. This leads to probabilities

$$\tilde{V}_m = \frac{1}{\mu_m} \ln\left(\sum_{j} \alpha_{jm} e^{V_j \mu_m}\right) \tag{5}$$

$$P(N_m) = \frac{e^{\tilde{V}_m}}{\sum e^{\tilde{V}_n}} \tag{6}$$

$$P(i|N_m) = \frac{\alpha_{im} e^{V_i \mu_m}}{\sum_j \alpha_{jm} e^{V_j \mu_m}} \tag{7}$$