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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

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

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

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

In the mixed cross-nested logit (MCNL) model we add an individual specific random Gaussian vector representing the personal bias of said individual in choosing alternatives. So for individual d the utility of alternative i at observation k is $W_{id} + \epsilon_{ik} = V_i + Z_{id} + \epsilon_{ik} = \beta \cdot x_i + Z_{id} + \epsilon_{ik}$ leading to a final probability for a series of observations k where individual d picks alternative i_k:

$$\int_Z p(Z) \prod_k P(i_k|Z) d\mathbb{P}_Z \tag{8}$$

Where $P(i_k|Z)$ is calculated like in the cross-nested model with V_j replaced by $W_{jd} = V_j + Z_{jd}$. We chose all Z_{id} to be iid normal distributed with mean zero and varinace σ^2. For a more detailed model description we refer you to the chapter in "The Handbook of Transportation Science" by Ben-Akiva and Bierlaire[11]

3.1. Data specification

Our data consists of statistics about the neighborhoods of Amsterdam from the Central Bureau of Statistics (CBS) and records of every instance of an EV charging at a public station in Amsterdam from the Charge Infrastructure Efficiency Model (CHIEF)[10] dataset. The municipality of Amsterdam gave approval to use the charging data of the public charging infrastructure installed between 2012 and November 2016. The Amsterdam University of Applied Science executed maintains the dataset as being part of the IDO-laad project (funded by Regieorgaan SIA). We used the program BIerlaires Optimization package for GEV Models Estimation (BIOGEME)[9], a specialized log-likelihood maximizer,to estimate nested, and cross-nested logit models to predict the probability of an EV driver choosing to charge in a particular neighborhood.

Data has been collected since 2014 on charging sessions of publicly accessible charging points within Amsterdam and is stored in the CHIEF database. Users are provided with a Radio-Frequency Identification (RFID) card by their charging provider which tracks their charging behaviour. Charging points can all be accessed by swiping a RFID card after which the user connects the charging cord to the socket. The session ends when the RFID card is swiped again and the charging cord is disconnected. The charging points belong to a number of different providers but can all be accessed with the same RFID card due to an implemented communication protocol. Users receive a monthly bill from their RFID providers and are charged per kWh. Depending on the charging point and RFID provider are also charged with a per session fee. Charging points are level 2 AC chargers capable of both 1 and 3-phase charging. The power supplied differs between the charging point.

We consider three groups of users: Regular users, participants in an electric carshare scheme and taxis. We later split the Regular Users into three subgroups based on when they charge during the day. These subgroups are Residents (people who predominantly charge at night and less during work hours), Commuters (people who predominantly charge during work hours and very rarely at night) and Visitors (people who only sporadically charge in Amsterdam)[8].

The properties of the neighborhoods used were the number of charging stations, the total number of inhabitants, the gender distribution of the inhabitants, the number of inhabitants aged between 0 and 14, between 15 and 24, between 25 and 44, between 45 and 64, and 65 and older, the average income per inhabitant, mean family size, the number of cars (electric or otherwise) per inhabitant, the percentage of homes built after the year 2000, the types of homes (own/rent), and the number of homes per inhabitant. The reason these properties were used is due to the fact that for these it is easier to estimate the changes due to large developmental projects ahead of the completion of said projects. In addition the other properties tracked by the CBS were either incomplete for some of the years considered or lacked relevance. The number of charging stations is excluded for the regular users due to the fact that the municipality had a policy where users could request charging stations in their neighborhood. Therefore the charge demand caused the number of charging stations and it therefore has no real predictive value. Once we split the Regular Users the number of charging stations is excluded for Residents only. The charging sessions used were those between 2014 and 2016, properties of neighborhoods differed by year and were lagged variables (i.e. we used properties from 2013 to predict demand for 2014), except for the number of charging stations, which differed by month and were unlagged. Vehicle properties used was the amount of times a vehicle charged in each neighborhood in the preceding month, except for the carshare participants no such properties were used since vehicles and drivers (and therefore choice) are almost completely independent due to the nature of the scheme. In the nested logit, every district was a nest, in the cross-nested logit we took the districts as nests, but allowed neighborhoods at the borders between districts to lie partially in the bordering district.

Charging sessions with no kWh charged or shorter than 5 minutes are not likely and irrelevant for the analysis and therefore considered as erroneous data. To our knowledge there or no EVs on the market with a battery package of over 100 kWh and therefore these charging sessions are left out of the dataset. Charging sessions longer than 28 days are outliers in the dataset and therefore considered not relevant. The analysis focus on in this paper the period in 2014-2016. After applying these filters 1.2 million sessions are left in the dataset. There are 958696 charge sessions for regular users, 192843 charge sessions for electric car-share scheme users and 41501 charge sessions for taxis.

4. Results

Table 1 outlines the goodness of fit (McFadden's adjusted rho-squared[11]) and the loglikelihood of our estimated models for various Nested Logit and Cross-nested logit for the three different classes of users. Table 2 outlines our estimates for the β-parameters for the Nested Logit Models for the three user classes which use all variables. Table 3 outlines the estimates of our nest coefficients for the three Nested models which use all variables. Table 4 outlines our estimates for the β-parameters for the Cross-Nested Logit Models for the three user classes. Table 5 outlines the estimates of our nest coefficients for the three Cross-Nested models. Table 6 contains for the Cross-Nested models the estimates of the alternative specific nest coefficients for the neighborhoods not solely in one nest. Each of these neighborhoods lie partially in two nests. These nests labeled Nest 1 (for the nest it belongs to in a geographic sense) and Nest 2 (for the nest it borders with) are neighborhood specific and specified in brackets after the neighborhood name. Then for each type of EV the first column contains the nest coefficient for Nest 1 and the second one the nest coefficient for Nest 2. Table 7 specifies for each nest the neighborhoods that always lie fully in those nests.

Next we ran CNL models on the 3 Regular User Types. The β-parameters, rho^2 and log-likelihood of these models are shown in Table 8, the α-coefficients in Table 9 in the same manner as Table 6, and the nest coefficients in Table 10. Finally we ran Mixed Cross-Nested models on sub-samples of 50 vehicles each of Taxi, Visitor, Commuter and Resident User Types. The comparisons of these results with the regular CNL models are shown in Table 11.

Table 1. General Results: Adjusted ρ^2, loglikelihood (LL) of the models (initial parameters are charging stations, age distribution and number of inhabitants),Reg=Regular users,EC=Electric Carshare Users

Model	Reg ρ^2	Reg LL	EC ρ^2	EC LL	Taxi ρ^2	Taxi LL
Nested Logit intitial	0.048	-4090360.649	0.068	-803084.505	0.138	-160300.733
Added gender dist.	0.048	-4089267.417	0.068	-802663.980	0.139	-160087.098
Added Mean Income	0.054	-4063780.103	0.068	-802483.814	0.146	-158893.907
Added Number of Homes	0.056	-4056884.496	0.073	-798778.738	0.151	-157912.492
Added Type of Homes	0.056	-4053871.441	0.073	-798728.637	0.147	-158723.814
Added Mean family size	0.057	-4050123.173	0.073	-798600.059	0.159	-156418.139
Added Number of Cars	0.063	-4024179.864	0.073	-798549.053	0.151	-157959.686
Added Age of Buildings	0.065	-4016640.304	0.073	-798536.964	0.165	-155289.557
Added Charging History	0.567	-1859030.715	N/A	N/A	0.662	-62916.721
Crossnested all variables	0.568	-1855226.444	0.079	-793617.262	0.667	-62041.528

5. Discussion of results

From other similar discrete choice model estimations it has been observed that for the purposes of practical applications of the model a McFadden's ρ^2 of around 0.1 indicates a good fit while a ρ^2 of between 0.2 and 0.4 indicates an excellent fit[12]. This would indicate that although it could be improved upon, our model for participants of an Electric Carshare scheme is adequate. Our Taxi and Regular User models appear to be excellent for practical applications.

We observe that charging history is the most important factor in predicting charging behaviour for most user-types. However for vehicles that are new to the system the other properties still predict reasonably well. Additionally the electric carshare vehicles have no connection between drivers and vehicles so any link with charging history is purely coincidental.

Table 2. Estimates β Parameters for the NL models, t-tests in brackets, N/A=not applicable

Parameters	Regular Users	Electric Carshare	Taxi
Number of Charging Stations	N/A	0.449 (72.42)	0.155 (7.76)
Total number of inhabitants	-1.98 (-10.15)	5.91 (15.83)	9.20 (5.16)
Aged 0-14	0.525 (48.09)	0.586 (35.78)	-0.796 (-11.88)
Aged 15-24	0.354 (41.46)	0.0316 (2.32)	0.196 (4.78)
Aged 25-44	-0.204 (-10.13)	-0.7 (-23.00)	-0.594 (-5.04)
Aged 45-64	-0.230 (-18.27)	-1.49 (-78.60)	-1.52 (-21.11)
Aged 65+	-0.159 (-22.97)	-0.0496 (-5.40)	0.633 (15.70)
Average income	0.665 (66.94)	0.0915 (6.07)	-0.839 (-13.55)
Total number of cars	0.957 (160.00)	0.104 (11.44)	-0.0776 (-1.60)
Total number of homes	2.16 (115.51)	2.09 (55.07)	1.10 (7.66)
Percentage of homes built after 2000	-0.0633 (-45.44)	-0.0106 (-4.95)	0.0467 (5.60)
Percentage rental homes	-0.120 (-8.24)	0.0360 (1.06)	1.91 (11.26)
Percentage homes owned by inhabitant	0.0430 (5.34)	0.149 (10.65)	1.11 (14.20)
Number of males	-0.622 (-5.71)	-1.72 (-7.91)	-3.04 (-3.11)
Number of females	-0.300 (-3.35)	-4.50 (-25.35)	-4.86 (-5.76)
Mean family size	-0.408 (-8.57)	-0.905 (-10.84)	5.84 (18.83)
Charging history	2.49 (1208.31)	N/A	2.06 (214.93)

Table 3. Estimates μ Nest Coefficients for the NL models, t-tests in brackets

Nests	Regular Users	Electric Carshare	Taxi
Amsterdam City Centre	1 (fixed)	1.01 (252.85)	1.48 (35.11)
Amsterdam North	1.65 (256.47)	2.01 (94.06)	1.39 (66.92)
Amsterdam West	1.36 (403.68)	1.23 (248.35)	1.11 (84.00)
Amsterdam New-West	1.41 (318.65)	1.93 (109.57)	1.01 (118.02)
Amsterdam Westpoort	1.84 (38.27)	1 (fixed)	1 (fixed)
Amsterdam East	1.06 (508.94)	1 (fixed)	1.04 (80.51)
Amsterdam SouthEast	1.96 (154.60)	15.8 (30.18)	1.48 (29.18)
Amsterdam South	1 (fixed)	1.15 (252.47)	1 (fixed)

Table 4. Estimates β Parameters for the CNL models, t-tests in brackets, N/A=not applicable

Parameters	Regular Users	Electric Carshare	Taxi
Number of Charging Stations	N/A	0.431 (76.00)	0.271 (14.88)
Total number of inhabitants	3.75 (14.86)	7.12 (15.00)	0.539 (1.35)
Aged 0-14	0.558 (52.58)	0.514 (33.34)	-0.685 (-12.01)
Aged 15-24	0.394 (45.36)	0.0862 (6.23)	0.283 (7.40)
Aged 25-44	-0.185 (-8.90)	-0.455 (-15.80)	0.482 (4.40)
Aged 45-64	-0.0526 (-4.14)	-1.25 (-64.08)	-0.968 (-14.51)
Aged 65+	-0.190 (-28.33)	-0.0261 (-3.09)	0.751 (20.05)
Average income	0.588 (60.47)	0.0983 (6.92)	-0.377 (-6.38)
Total number of cars	0.813 (133.68)	0.209 (25.92)	0.00857 (0.22)
Total number of homes	2.16 (115.10)	1.94 (61.22)	0.416 (4.07)
Percentage of homes built after 2000	-0.0299 (-21.46)	-0.0420 (-20.50)	0.0276 (3.41)
Percentage rental homes	-0.143 (-10.26)	-0.0128 (-0.39)	1.32 (8.23)
Percentage homes owned by inhabitant	-0.000305 (-0.04)	0.143 (9.74)	0.652 (8.31)
Number of males	-4.02 (-29.59)	-3.03 (-12.06)	0.0735 (-0.21)
Number of females	-2.80 (-23.74)	-4.86 (-21.10)	-0.774 (-5.26)
Mean family size	-0.188 (-4.01)	-0.0373 (-4.97)	5.41 (21.87)
Charging history	2.41 (1179.67)	N/A	1.93 (214.63)

Our results also showed that some neighborhoods were far more correlated with other districts than the one they were located in and that this vastly differed for the different kinds of user-type (the Hoofddorppleinbuurt being in the South nest entirely when considering Regular users but in the New-West district entirely when considering Carshare

Table 5. Estimates μ Nest Coefficients for the CNL models, t-tests in brackets

Nests	Regular Users	Electric Carshare	Taxi
Amsterdam City Centre	1 (fixed)	1.04 (270.04)	2.18 (26.59)
Amsterdam North	1.79 (255.62)	2.41 (86.55)	1.55 (65.95)
Amsterdam West	1.46 (336.79)	1.24 (251.31)	1.26 (72.70)
Amsterdam New-West	1.52 (306.36)	3.08 (70.83)	1.10 (120.60)
Amsterdam Westpoort	1.90 (26.28)	1 (fixed)	3.68 (29.61)
Amsterdam East	1.21 (448.34)	1 (fixed)	1 (fixed)
Amsterdam SouthEast	2.11 (158.09)	20.1 (31.02)	1.68 (29.36)
Amsterdam South	1 (fixed)	1.35 (222.92)	1.83 (48.68)

Table 6. Estimates α Nest coefficents for neighborhoods in more than 1 nest for the CNL models (reg=Regular users)

Neighborhood (Nest 1/Nest 2)	Reg 1	Reg 2	Carshare 1	Carshare 2	Taxi 1	Taxi 2
Haarlemmerbuurt (City Centre/West)	0	1	0.785	0.215	1	0
Jordaan (City Centre/West)	1	0	1	0	0.00865	0.99135
Weteringschans (City Centre/South)	0.5	0.5	0.924	0.076	0	1
Weesperbuurt en Plantage (City Centre/East)	1	0	1	0	0.975	0.025
Oostelijke Eilanden en Kadijken (City Centre/East)	0	1	1	0	1	0
Frederik Hendrikbuurt (West/City Centre)	1	0	0.99957	0.00043	0.062	0.938
Da Costabuurt (West/City Centre)	0.724	0.276	0.9999	0.0001	0.665	0.335
Overtoomse Sluis (West/South)	0.804	0.196	0.885	0.115	0.0411	0.9589
Vondelbuurt (West/South)	1	0	0.226	0.774	0.0258	0.9742
De Kolenkit (West/New-West)	0.512	0.488	0.670	0.330	1	0
Van Galenbuurt (West/New-West)	0.404	0.596	0.00435	0.99565	0.965	0.035
Hoofdweg en Omgeving (West/New-West)	0.290	0.710	1	0	0.0348	0.9652
Westindische buurt (West/New-West)	0.306	0.694	0.938	0.062	0.484	0.516
Slotermeer-Noordoost (New-West/West)	0.519	0.481	0.805	0.195	0.999	0.001
Overtoomse Veld (New-West/West)	0	1	0	1	1	0
Westlandgracht (New-West/South)	0.978	0.022	0	1	0.508	0.492
Oude Pijp (South/City Centre)	0.5	0.5	0.242	0.758	1	0
Diamantbuurt (South/East)	0	1	0.9825	0.0175	1	0
Hoofddorppleinbuurt (South/New-West)	0.445	0.555	0.0001	0.9999	0.0116	0.9884
Willemspark (South/West)	1	0	0.697	0.303	0.951	0 .049
IJselbuurt (South/East)	0	1	1	0	1	0
Rijnbuurt (South/East)	0	1	0.370	0.630	0.843	0.157
Buitenveldert Oost (South/East)	1	0	0.739	0.261	0	1
Weesperzijde (East/South)	1	0	0.0001	0.9999	0	1
Oosterparkbuurt (East/City Centre)	0	1	1	0	0.326	0.674
Dapperbuurt (East/City Centre)	0.951	0.049	0.0001	0.9999	0.135	0.865
Oostelijk Havengebied (East/City Centre)	0.974	0.026	0	1	0	1
De Omval (East/South)	0.880	0.120	1	0	0	1

users for example). A possible explanation in the case of the Diamantbuurt is that the South district is a more expensive district than the New-West district, so the regular users (who tend to be more affluent) tend to be in the South district more than Electric Carshare participants (who tend to be less affluent).

6. Conclusion

We have generated models to estimate the distribution of charging demand for five different user-types for a given year by using data of the previous year. Using these models we should be able to make reasonable predictions of the distribution of charging demand in the coming year, even in the event that the makeup of a neighborhood changes significantly (for example when the Jordaan went from a low/average income neighborhood to a high income one) or in the case that new neighborhoods arise (through development projects). This way the city will be able to place charging infrastructure to accommodate this change in demand. It appears the added value of Cross-Nested models in comparison to the regular Nested models pale in comparison to the added value of adding in personal preference in the form of either charging history or a Mixed Model. In the future we will look into the possibility of running our

Table 7. Location of neighborhoods limited to being in a specific nest in the CNL models

Nests	Neighborhoods
Amsterdam City Centre	Burgwallen-Oude Zijde, Burgwallen-Nieuwe Zijde, Grachtengordel-West, Grachtengordel-Zuid, Nieuwmarkt en Lastage
Amsterdam North	Volewijck, IJplein en Vogelbuurt, Tuindorp Nieuwendam, Tuindorp Buiksloot, Nieuwendammerdijk en Buiksloterdijk, Tuindorp Oostzaan, Oostzanerwerf, Kadoelen, Nieuwendam-Noord, Buikslotermeer, Banne Buiksloot, Buiksloterham, Nieuwendammerham, Waterland
Amsterdam West	Houthavens, Spaarndammer- en Zeeheldenbuurt, Staatsliedenbuurt, Centrale Markt, Kinkerbuurt, Van Lennepbuurt, Helmersbuurt, Sloterdijk, Landlust, Erasmuspark, De Krommert
Amsterdam New-West	Slotermeer-Zuidwest, Geuzenveld, Eendracht, Lutkemeer en Ookmeer, Osdorp-Oost, Osdorp-Midden, De Punt, Middelveldsche Akerpolder en Sloten, Slotervaart, Sloten- en Riekerpolder
Amsterdam Westpoort	Westelijk Havengebied, Bedrijventerrein Sloterdijk
Amsterdam East	Indische Buurt West, Indische Buurt Oost, Zeeburgereiland en Nieuwe Diep, IJburg West, IJburg Zuid, Transvaalbuurt, Frankendael, Middenmeer, Betondorp,
Amsterdam SouthEast	Amstel III en Bullewijk, Bijlmer-Centrum D, F en H, Bijlmer-Oost E,G en K, Nellestein, Holendrecht en Reigersbos, Gein, Driemond
Amsterdam South	Nieuwe Pijp, Schinkelbuurt, Museumkwartier, Stadionbuurt, Apollobuurt, Duivelseiland, Scheldebuurt, Station-Zuid WTC en omgeving, Buitenveldert-West

Table 8. Attribute Parameters, ρ^2 and log-likelihood of CNL Regular User Types

Parameters	Visitors	Commuter	Resident
Number of Charging Stations	0.674 (42.56)	0.480 (86.38)	N/A
Total number of inhabitants	1.12 (0.00)	9.36 (34.40)	-0.358 (-1.51)
Aged 0-14	0.234 (5.58)	0.672 (43.75)	0.474 (30.79)
Aged 15-24	0.119 (3.48)	0.187 (16.19)	0.339 (27.81)
Aged 25-44	0.0681 (0.76)	-0.966 (-35.04)	0.403 (13.74)
Aged 45-64	-0.0622 (-1.12)	-0.609 (-36.42)	0.232 (12.47)
Aged 65+	0.0369 (1.33)	-0.209 (-22.36)	-0.136 (-13.71)
Average income	0.531 (13.92)	0.0887 (6.33)	0.712 (52.04)
Total number of cars	0.0242 (1.00)	0.683 (73.09)	0.647 (75.12)
Total number of homes	1.70 (21.53)	1.57 (59.26)	1.78 (65.82)
Percentage of homes built after 2000	-0.0191 (-3.62)	-0.00498 (-2.52)	-0.0689 (-35.17)
Percentage rental homes	0.175 (1.90)	0.183 (8.47)	-0.317 (-17.65)
Percentage homes owned by inhabitant	-0.00131 (-0.03)	-0.0332 (-3.11)	0.0137 (1.26)
Number of males	-0.718 (-0.00)	-6.77 (-43.37)	-2.07 (-15.89)
Number of females	-2.46 (-101.42)	-3.82 (-30.01)	-0.848 (-8.14)
Mean family size	1.78 (9.33)	-1.06 (-15.93)	-0.218 (-3.16)
Charging history	3.16 (171.20)	2.01 (531.59)	2.55 (955.55)
ρ^2	0.235	0.399	0.664
Log-Likelihood	-152493.343	-672873.593	-1000572.127

Table 9. Estimates μ Nest Coefficients for the CNL models of the Regular User Types (t-tests in brackets)

Nests	Visitors	Commuters	Residents
Amsterdam City Centre	1 (fixed)	1 (fixed)	1 (fixed)
Amsterdam North	2.15 (48.47)	2.08 (141.69)	1.53 (205.12)
Amsterdam West	1.32 (103.76)	1.80 (158.76)	1.35 (305.10)
Amsterdam New-West	1.85 (46.73)	2.34 (121.75)	1.24 (251.91)
Amsterdam Westpoort	1.59 (5.19)	4.02 (13.97)	1.68 (22.07)
Amsterdam East	1.29 (108.03)	1.28 (245.65)	1.17 (364.00)
Amsterdam SouthEast	1.92 (36.17)	2.07 (87.64)	1.92 (117.52)
Amsterdam South	1 (fixed)	1.18 (274.97)	1 (fixed)

Mixed Models on larger samples of vehicles to get a more accurate estimate. Additionally it would prove very useful to get estimates of the amount of vehicles leaving the system and the amount of new vehicles entering the system.

Table 10. Estimates α Nest coefficents for neighborhoods in more than 1 nest for Regular User Types, Vis=Visitor, Com=Commuter, Res=Resident

Neighborhood (Nest 1/Nest 2)	Vis 1	Vis 2	Com 1	Com 2	Res 1	Res 2
Haarlemmerbuurt (City Centre/West)	0	1	0	1	0	1
Jordaan (City Centre/West)	1	0	1	0	1	0
Weteringschans (City Centre/South)	1	0	1	0	0.996	0.004
Weesperbuurt en Plantage (City Centre/East)	1	0	1	0	1	0
Oostelijke Eilanden en Kadijken (City Centre/East)	0	1	0	1	0	1
Frederik Hendrikbuurt (West/City Centre)	1	0	1	0	1	0
Da Costabuurt (West/City Centre)	0.624	0.376	0.644	0.356	0.763	0.237
Overtoomse Sluis (West/South)	0.948	0.052	0.978	0.022	0.669	0.331
Vondelbuurt (West/South)	1	0	0.524	0.476	1	0
De Kolenkit (West/New-West)	0.530	0.470	0.441	0.559	1	0
Van Galenbuurt (West/New-West)	0.0881	0.9119	0.109	0.891	0.744	0.256
Hoofdweg en Omgeving (West/New-West)	0.971	0.029	0	1	0.481	0.519
Westindische buurt (West/New-West)	1	0	0.761	0.239	0.650	0.350
Slotermeer-Noordoost (New-West/West)	0.781	0.219	0.002	0.998	0.282	0.718
Overtoomse Veld (New-West/West)	0	1	0	1	0	1
Westlandgracht (New-West/South)	0.984	0.016	0.0251	0.9749	0.861	0.139
Oude Pijp (South/City Centre)	0.000112	0.999888	0	1	0.008	0.992
Diamantbuurt (South/East)	0	1	0.307	0.693	0	1
Hoofddorppleinbuurt (South/New-West)	0.325	0.675	0.00994	0.99006	0.988	0.012
Willemspark (South/West)	0	1	0	1	0.990	0.010
IJselbuurt (South/East)	0	1	0.353	0.647	0	1
Rijnbuurt (South/East)	0	1	0.150	0.850	0	1
Buitenveldert Oost (South/East)	0.458	0.542	1	0	1	0
Weesperzijde (East/South)	0.688	0.312	1	0	1	0
Oosterparkbuurt (East/City Centre)	0.0874	0.9126	0	1	0	1
Dapperbuurt (East/City Centre)	0.961	0.039	1	0	0.844	0.156
Oostelijk Havengebied (East/City Centre)	1	0	0.945	0.055	1	0
De Omval (East/South)	0.518	0.482	0.575	0.425	0.963	0.037

Table 11. Results CNL and MCNL models on a subsample of 50 vehicles

	Taxi	Visitor	Commuter	Resident
CNL ρ^2	0.617	0.150	0.463	0.723
CNL LL	-4801.194	-1095.948	-1648.012	-2948.405
MCNL ρ^2	0.669	0.184	0.537	0.752
MCNL LL	-4148.467	-1051.488	-1420.915	-2637.426
MCNL Variance Parameter	1.08(27.25)	0.895(11.68)	0.995 (20.50)	1.04 (23.32)

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