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DOI
10.1016/j.trd.2019.102206

Publication date
2020

Document Version
Final published version

Published in
Transportation Research Part D: Transport and Environment

Transportation Research Part D 78 (2020) 102206

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands

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A R T I C L E I N F O

Keywords:
Electric traveling
Electric vehicles
BEV
Route choice
Charging behavior

A B S T R A C T

Electric travelling appears to dominate the transport sector in the near future due to the needed transition from internal combustion vehicles (ICV) towards Electric Vehicles (EV) to tackle urban pollution. Given this trend, investigation of the EV drivers' travel behaviour is of great importance to stakeholders including planners and policymakers, for example in order to locate charging stations. This research explores the Battery Electric Vehicle (BEV) drivers route choice and charging preferences through a Stated Preference (SP) survey. Collecting data from 505 EV drivers in the Netherlands, we report the results of estimating a Mixed Logit (ML) model for those choices. Respondents were requested to choose a route among six alternatives: freeways, arterial ways, and local streets with and without fast charging. Our findings suggest that the classic route attributes (travel time and travel cost), vehicle-related variables (state-of-charge at the origin and destination) and charging characteristics (availability of a slow charging point at the destination, fast charging duration, waiting time in the queue of a fast-charging station) can influence the BEV drivers route choice and charging behaviour significantly. When the state-of-charge (SOC) at the origin is high and a slow charger at the destination is available, routes without fast charging are likely to be preferred. Moreover, local streets (associated with slow speeds and less energy consumption) could be preferred if the SOC at the destination is expected to be low while arterial ways might be selected when a driver must recharge his/her car during the trip via fast charging.

1. Introduction

The transport sector is recognised as one of the primary drivers of energy consumption and Greenhouse Gas (GHG) emissions with 23% of the total emissions in Europe in 2015 (EuroStat Greenhouse Gas Emission Statistics, 2017) and also the only sector which demonstrates an increase in the last years (European Commission, 2016; McKinsey, 2016; Taefi et al., 2016). This is contributing to climate change which might be aggravated in the future if the trend is not controlled.

According to an urgent need to address fossil fuel dependency, air pollution, global warming, and mitigate public concerns on health issues a transition from internal combustion vehicles (ICV) towards alternative technologies is required. Electrification of vehicles is a major measure to increase travel energy efficiency as well as resource security and decarbonisation of transport leading to climate protection and less pollution.

In recent years, the electric vehicles (EV) market share has significantly grown. Researchers, policymakers, and the involved business firms try massively to stimulate travellers to adopt electric mobility. Based on the technical specification, EVs are categorised into Hybrid Electric Vehicles (HEV), Plug-in Hybrid Electric Vehicles (PHEV), Battery Electric Vehicles (BEV), Fuel-Cell Electric

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https://doi.org/10.1016/j.trd.2019.102206

Vehicles (FCEV) (Cavallaro et al., 2018; Gong et al., 2016; Li et al., 2020).

PHEVs and BEVs have been dominating the EV market share. PHEVs are similar to HEVs with having a more powerful battery which can also be charged at a station while BEVs use high-capacity electric engines that must always be recharged through a charger. Compared with HEVs and PHEVs, BEVs have the highest battery capacity, therefore, the greatest range with the lowest local emission due to not burning any fuel. BEV models are mostly found on the market as small and mid-size cars which reflects the fact that BEVs are usually used for short-distance commuting trips, while PHEVs are bigger and used for long-distance trips since the range is always guaranteed by the internal combustion engine.

In some countries, such as the Netherlands, policymakers incentivised users to purchase PHEVs at early stages of electric travelling, then the strategy shifted towards phasing out the sale of PHEVs, due to their size and limited impact on lowering emissions, and promoting BEVs given the higher battery capacity and lower emissions (International and Agency, 2018). However, BEVs have several restrictions such as lower driving range, higher recharging duration, and lack of charging infrastructure. That is why low State-of-Charge (SOC) and lack of charging opportunities are the main concerns of the EV drivers. It is the so-called “range anxiety” which refers to the concern that the battery would get depleted during a trip before arriving at the destination or reaching a charging station (Esmaili et al., 2018; Guo et al., 2018; Noel et al., 2019; Pearre et al., 2011).

Charging stations can be categorised into private, semi-public, and public ones. Private and semi-public charging refers to the charging points installed at home or workplace while public chargers are installed at public places including airports, railway stations, shopping malls, traffic hotspots, highways, parking lots. Charging points are also classified into slow and fast charging based on the recharging time. The former takes longer to recharge an EV. On average, a BEV needs 6–8 h and 20–40 min to be recharged with a slow charger and a fast charger, respectively (Botsford and Szczepanek, 2009).

Route choice as one of the central topics in transport research has been studied for decades. Empirical research on route choice behaviour shed light on the attributes influencing the route selection of drivers (Abdel-Aty et al., 1997; Arnott et al., 1992; Gao et al., 2010; Wu et al., 2018; Xu et al., 2011). Discrete choice modelling is the the most frequently used methodology in the literature to unravel the route choice behaviour of individuals (Dalumpines and Scott, 2017; Emmerink et al., 1996; Habib et al., 2013; Pillat et al., 2011; Prato, 2009; Tawfik and Rakha, 2013). The identified factors can be categorized into route attributes, traffic information, trip specifications, drivers’ attitudes and socio-demographic characteristics. Li et al. (2005) studied commute route choice of 182 drivers. They reported that commuters are usually more flexible in terms of departure time and route choice in the evening than in the morning commute. Estimating a hybrid choice model, Alizadeh et al. (2019) examined the heterogeneity amongst drivers and concluded that frequent car users have different route choice behaviour compared to occasional ones. They also pointed out that incorporating drivers’ characteristics and latent variables significantly increase the model explanatory power. These results could highlight the importance of exploring the EV drivers’ route choice behaviour due to the heterogeneity between EV and ICV drivers.

Charging specific to the behaviour of EV drivers (Azadfar et al., 2015). The charging behaviour of EV drivers has been investigated in two dimensions: slow charging and fast charging. Slow charging is usually used when a driver intends to stay (possibly for a longer periods) at a particular place such as his/her home or job location while fast charging points have been mostly installed in the main streets and freeways to enable EV drivers to recharge their cars during their trips which are similar to today’s gas stations (Azadfar et al., 2015; Morrow et al., 2008). According to the findings of Chang et al. (2012), fast charging opportunity is the crucial element for the development and adoption of EVs. It was observed that fast charging could potentially reduce range anxiety and increase driving distance. Using stated preference experiments, Jabeen et al. (2013) explored the charging preferences of EV drivers in the Western Australia Electric Vehicle pilot. They concluded that charging at home or work is generally preferred while drivers who need to pick up/drop off a family member tend to use fast charging. Overall, it was found that drivers are sensitive to charging costs and duration. This shows the necessity of including both fast charging and slow charging in the analysis of EV drivers’ charging behaviour.

There is a growing body of literature that explores the implications of electric travelling in both demand and supply sides of transport systems. On the demand side, some studies have investigated the mode choice of travellers in the era of electrification (Carley et al., 2013; Jensen et al., 2013; Liao et al., 2017; Lieven et al., 2011; Nazari et al., 2019; Rasouli and Timmermans, 2016; Rezvani et al., 2015). Furthermore, many researchers have focused on the supply side and the role of EV specifications and corresponding infrastructure needs in the EV adoption where most of them assume that the EV drivers’ route choice behaviour is similar to ICV car drivers (Cavadas et al., 2015; Çetinkaya, 2018; Csiszár et al., 2019; Sun et al., 2018; Zhu et al., 2016).

In general, several factors including cruising range limitation, recharging duration and frequency, charging methods, availability and accessibility of charging points can lead to a distinctive travel behaviour of EV drivers when compared to ICV which is fairly missing in the literature. This uncertainty can lead to challenges for policymakers and service suppliers. Given the growth in the fleet of EVs all around the world, more insights into the behaviour of EV drivers are needed in order to address the existing issues and also plan the required measures.

In this study, a stated preference survey is conducted to investigate the BEV drivers’ route choice and charging behaviour. Routes are divided into freeways, arterial ways, and local streets. They can be equipped with a fast-charging point which can be the underlying reason for different route preferences. Therefore, three experiments with unique specifications have been set up to identify the most effective factors including route attributes, vehicle-related specifications, and charging characteristics that influence the drivers to select routes with/without fast charging. The next sections describe the study specifications, survey design and structure, data collection, modelling, results, and conclusions.

2. Study specifications

We categorised route alternatives into three groups: freeways, arterial ways, and local streets. On the other hand, slow charging and fast charging are currently two common charging methods. Literature shows that fast charging may affect route choice behaviour while slow charging has a minimal effect (Yang et al., 2016). This is because fast charging increases the flexibility of users in terms of charging time and location similar to what happens with ICV cars. However, the charging frequency and duration of a BEV is still higher than refuelling an ICV car and what is more charging points are available on a relatively lower number when compared to gas stations nowadays. Therefore, routes can be divided into routes with and without fast charging. It should be noted that statistics show that EVs are mostly used for making short commuting trips at the present time in the Netherlands (Centraal Bureau voor de Statistiek (CBS), 2016). Therefore, respondents were requested to consider a commuter trip and to select between six routes namely freeway, arterial way, and local streets (different speeds and consumptions associated) with and without fast charging.

SOC at the origin, electricity consumption, travel time, and travel cost were considered as attributes of all routes while recharging duration, waiting time in the queue of a charging point, and charger location were alternative-specific attributes of the routes for which respondents could opt for a fast-charging station in the middle of the way. Since the driving range and refuelling duration of BEVs are significantly different from ICV cars, BEV drivers are expected to show a route choice behaviour that is different from ICV. For example, Yang et al. (2016) suggest that the most efficient electricity consumption is derived at the speed range of 30–70 km/h in a congested area thanks to Regenerative Braking System (RBS). Furthermore, range anxiety is another determinant that may limit the possible trip chain and route selection. To illustrate, one might either select a route with lower consumption but higher travel time in order to ensure that a certain minimum level of battery power is available at the end of the trip or deviate and choose another route because of the availability of a fast charging point.

Therefore, we hypothesise that SOC at the origin and destination of a trip are important indicators that can influence the drivers' decision on the route and charging behaviour. In the survey instrument, the SOC at the destination is derived from subtracting the initial SOC and the electricity consumption. When the SOC at the destination approaches zero a significantly different driving behaviour is expected to be observed, especially for those who have high range anxiety.

On the other hand, the availability of a charging point at the destination may play an important role in route and charging choices of drivers, especially in commuting trips. This is because when people park their cars for several hours in a particular location, they may prefer to take advantage of that time for recharging their BEVs. Otherwise, they must ensure that they have sufficient battery power for performing the return trips. Therefore, the availability of a slow charger at the destination is incorporated in the survey as a context variable.

If one prefers to recharge his/her vehicle during a trip, fast charging can be a possible option. Fast charging increases the flexibility of drivers in charging time and location. It can be located closer to the origin, in the middle of the way, or closer to the destination. Therefore, fast charging duration, waiting time in the queue and charging station location were considered in the routes with fast charging as relevant attributes.

Travel time and travel cost are classic route attributes whereas EV attributes and charging characteristics are specific to electric mobility. Respondents were explained that if they select a route with fast charging, they must recharge their car during the trip. Moreover, since fast charging cost is higher than slow charging (roughly twice depending on charging speed and capacity of the infrastructure), the associated cost was embedded in the travel cost of those routes.

3. Survey design

It is desirable to define attributes and attribute levels in the SP experiment based on real circumstances. To achieve this, attribute levels are pivoted on the analysis of the real data provided by CBS for conducting a commuting trip of 40 km with a BEV.

Fiori et al. (2017) concluded that BEV energy consumption increases in the routes with higher speed. Based on the speed range, we assumed that travel time is lower in freeways compared to arterial ways and local streets while electricity consumption and travel cost are higher in freeways than arterial ways and local streets assuming a similar distance in the alternatives. Moreover, fast charging during a trip increases total charging time and cost in the freeway compared to arterial way and local streets due to lower SOC at the time of charging.

Based on the SOC at the origin and electricity consumption, three possible scenarios can be considered:

1. SOC at the origin is much higher than electricity consumption during the trip (designated as Green Zone).
2. SOC at the origin and electricity consumption are roughly equivalent (designated as Grey Zone).
3. SOC at the origin is lower than or equal to electricity consumption (designated as Red Zone).

We named the first case as "Green Zone" because drivers are not obliged to recharge their vehicles during the trip according to the SOC they will have at the destination which is equal to or more than 50% in the case they do not use fast charging. It implies that they can make the return trip without charging. However, the availability of a slow charger at the destination can be a determinant to choose fast charging in the return trip in order to ensure that that trip can be done.

In the second scenario, which we called "Grey Zone", SOC at the destination is between 0 and 35% without fast charging. In this condition, users may prefer only the routes with fast charging depending on the range anxiety level, attitudes, and socio-economic characteristics.

On the other hand, there is no option for selecting a route where no fast charging takes place on what is designated as "Red Zone",

Table 1
Characteristics of Experiment 1 (green zone).

Experiment 1

Level of battery at origin [80%, 85%, 90%]
Availability of slow charger at the destination [YES, NO]

Attributes \ Alternatives	Routes without fast charging: Mostly freeway	Routes without fast charging: Mostly Arterial way	Routes without fast charging: Mostly Local Streets	Route with fast charging: Mostly freeway with charging	Route with fast charging: Mostly Arterial way with charging	Route with fast charging: Mostly Local Streets with charging
Percentage of battery capacity consumed for making your trip	20,25,30	15,20,25	10,15,20	20,25,30	15,20,25	10,15,20
Travel Costs (euro)	3,3.5,4	2,2.5,3	1,1.5,2	6,6.5,7	5,5.5,6	4,4.5,5
Travel Time excluding charging time (min)	20,25,30	25,30,35	30,35,40	20,25,30	25,30,35	30,35,40
Charging time to be fully charged (min)				10,12,14	8,10,12	6,8,10
Waiting time in the charging queue				3,6,9	3,6,9	3,6,9
Charging Location				Close to origin, in the middle, close to destination	Close to origin, in the middle, close to destination	Close to origin, in the middle, close to destination

which is the third scenario. In this case, a trip cannot be done without fast charging since the car would run out of power.

To address all the aforementioned scenarios, three different experiments were designed: Green, Grey and Red zones. It is postulated that a commuting trip is performed between a certain origin-destination pair in all experiments, so travel distance and purpose are assumed to be fixed. SOC at the origin differs significantly in each experiment, for example, 90% in Green Zone, 30% in Grey Zone, and 15% in Red Zone. It is assumed that if a traveller selects a route with fast charging, he/she has to recharge his/her car with the fast charger point. Each experiment has 24 treatment combinations in 6 blocks of 4 choice tasks. Several constraints were imposed to ensure all choice sets are feasible. Tables 1–3 show the characteristics of the experiments and the associated attribute levels.

Due to the number of attributes and attribute levels, fractional factorial experimental design is used in order to decrease the total number of choice sets per experiment. The efficient design was selected to minimise the standard errors of the parameter estimates in

Table 2
Characteristics of Experiment 2 (grey zone).

Experiment 2

Level of battery at origin [30%, 40%, 50%]
Availability of slow charger at the destination [YES, NO]

Attributes \ Alternatives	Routes without fast charging: Mostly freeway	Routes without fast charging: Mostly Arterial way	Routes without fast charging: Mostly Local Streets	Route with fast charging: Mostly freeway with charging	Route with fast charging: Mostly Arterial way with charging	Route with fast charging: Mostly Local Streets with charging
Percentage of battery capacity consumed for making your trip	25,30,35	20,25,30	15,20,25	25,30,35	20,25,30	15,20,25
Travel Costs (euro)	3.5,4,4.5	2.5,3,3.5	1.5,2,2.5	6.5,7,7.5	5.5,6,6.5	4.5,5,5.5
Travel Time excluding charging time (min)	20,25,30	25,30,35	30,35,40	20,25,30	25,30,35	30,35,40
Charging time to be fully charged (min)				14,16,18	12,14,16	10,12,14
Waiting time in the charging queue				3,6,9	3,6,9	3,6,9
Charging Location				Close to origin, in the middle, close to destination	Close to origin, in the middle, close to destination	Close to origin, in the middle, close to destination

Table 3
Characteristics of Experiment 3 (red zone).

Experiment 3

Level of battery at origin [30%, 40%, 50%]
Availability of slow charger at the destination [YES, NO]

Attributes / Alternatives	Route WITH fast charging		
	Mostly freeway with charging	Mostly Arterial way with charging	Mostly Local Streets with charging
Percentage of battery capacity consumed for making your trip	30,35,40	25,30,35	20,25,30
Travel Costs (euro)	7,7.5,8	6,6.5,7	5,5.5,6
Travel time excluding charging time (min)	20,25,30	25,30,35	30,35,40
Charging time to be fully charged (min)	20,22,24	18,20,22	16,18,20
Waiting time in the charging queue	3,6,9	3,6,9	3,6,9
Charging Location	Close to the origin, in the middle, close to the destination	Close to the origin, in the middle, close to the destination	Close to the origin, in the middle, close to the destination

case the asymptotic variance-covariance (AVC) matrix is determined (ChoiceMetrics, 2012). This method aims at minimising so-called $D_p - error$ (Bliemer and Rose, 2010):

$$D_p - error = \det(\Omega_1(X, \beta))^{1/K}$$

where K indicates the number of parameters to be estimated. β is set to the best estimation of parameters, assuming they are correct. To obtain priors, a pilot study was conducted, then the survey was redesigned accordingly. The choice experiments have been constructed using the software package NGENE (ChoiceMetrics, 2012).

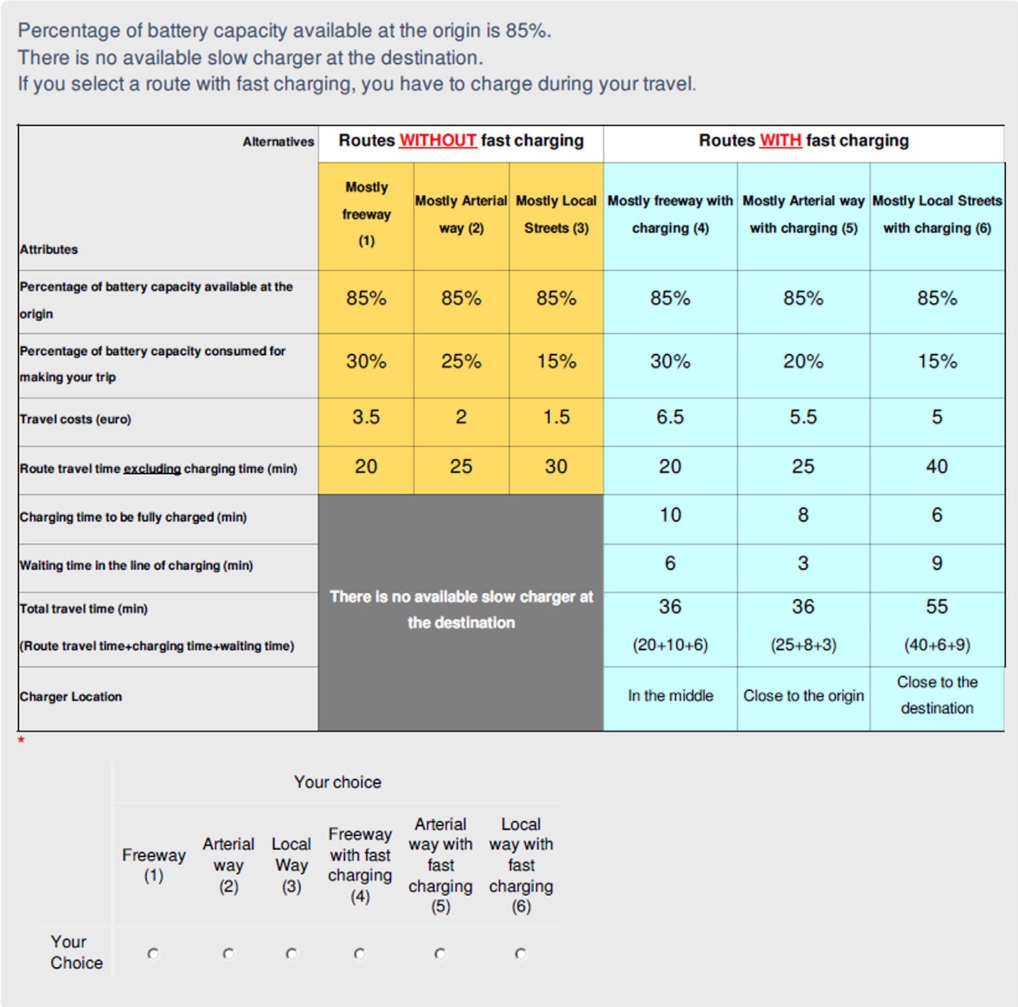
4. Survey structure

The questionnaire consists of three parts including: individual mobility behaviour, stated choice experiments, and socio-economic characteristics of the participants. Each respondent was confronted with four choice tasks for each experiment. To achieve more reliable results, only EV users were incorporated into this study. Thus, two screening questions were asked at first to filter the respondents: if they had a driving license and if they drove an EV frequently. To avoid bias in the responses, the blocks of each experiment were randomly distributed among participants. Fig. 1 illustrates an example of a choice set that as shown to each respondent.

5. Data

It was challenging to obtain the required number of complete responses given that EV drivers are still a low percentage. Although we set up an SP survey to consider a commuting trip being performed with a BEV, the data obtained from BEV, PHEV, and HEV drivers were incorporated due to the fact that the number of BEV drivers is significantly lower than the hybrid (PEHV and HEV). In total, the data of 505 respondents were collected. Fig. 2 shows the data composition in some key variables.

As shown, male respondents outnumber the female ones. The respondents are mostly between the ages of 18 and 45 years old, having a (advanced) diploma and earning 1000–5000 euros monthly net income. This would suggest the characteristics of EV adopters in the population. We achieved a sample of 140, 231, 107, and 27 of the BEV, PHEV, HEV, FCEV drivers. BEV and PHEV drivers who are the ones who have to recharge their cars were asked about their car specifications such as driving range and their current charging behaviour including charging method, location, time, etc, depicted in Fig. 3.



Percentage of battery capacity available at the origin is 85%.
There is no available slow charger at the destination.
If you select a route with fast charging, you have to charge during your travel.

Alternatives / Attributes	Routes WITHOUT fast charging: Mostly freeway (1)	Mostly Arterial way (2)	Mostly Local Streets (3)	Routes WITH fast charging: Mostly freeway with charging (4)	Mostly Arterial way with charging (5)	Mostly Local Streets with charging (6)
Percentage of battery capacity available at the origin	85%	85%	85%	85%	85%	85%
Percentage of battery capacity consumed for making your trip	30%	25%	15%	30%	20%	15%
Travel costs (euro)	3.5	2	1.5	6.5	5.5	5
Route travel time excluding charging time (min)	20	25	30	20	25	40
Charging time to be fully charged (min)	There is no available slow charger at the destination			10	8	6
Waiting time in the line of charging (min)				6	3	9
Total travel time (min) (Route travel time+charging time+waiting time)				36 (20+10+6)	36 (25+8+3)	55 (40+6+9)
Charger Location				In the middle	Close to the origin	Close to the destination

*

Your choice	Freeway (1)	Arterial way (2)	Local Way (3)	Freeway with fast charging (4)	Arterial way with fast charging (5)	Local way with fast charging (6)
Your Choice	○	○	○	○	○	○

Fig. 1. Example of a choice set in Experiment 1.

Participants experience various driving ranges from less than 100 km to more than 500 km. Around 80% of those who use slow charging take 4–8 h on average to recharge their vehicle. They mostly recharge their car at home and workplace by 50% and 29%, respectively. 65% of the EV drivers plug in their cars when SOC is above 50%. It might represent their high range anxiety or their charging pattern to recharge their vehicle when they arrive at the destination regardless of the SOC.

Dataset analysis represented in Fig. 4 shows that 57% of the respondents prefer the routes with fast charging in the green zone where SOC at the origin is always equal or higher than 50%. In the grey zone, the number of drivers choosing the routes with fast charging increases, as expected. However, if a driver tends to select routes without fast charging, local streets are more likely to be chosen. This is because the consumption is lower in local street resulting in higher SOC at the destination. While freeways are favoured in the case of preference for selecting a route with fast charging owing to lower travel time. On the other hand, arterial ways are preferred in the red zone. This might be because of the median travel time and cost.

6. Discrete choice modelling

Random Utility Maximization (RUM) which is a sub-category of discrete choice modelling is one of the most popular frameworks to explore the travellers' preference towards route choice. It hypothesizes that each individual chooses a specific alternative i when the associated utility is the highest compared to the other options (McFadden, 1974; Ortúzar and Willumsen, 2011). The utility functions for all alternatives are defined using Eq. (1).

$$U_i = \sum_m \beta_{im}.\, x_{im} + \sum_k \beta_{ik}.\, x_{ik} + \varepsilon_i \tag{1}$$

where the first component of the utility function is associated with the instrumental attributes that were presented in the SP choice sets such as route, vehicle-related, and charging attributes as depicted in Tables 1–3. It should be mentioned that SOC at the origin

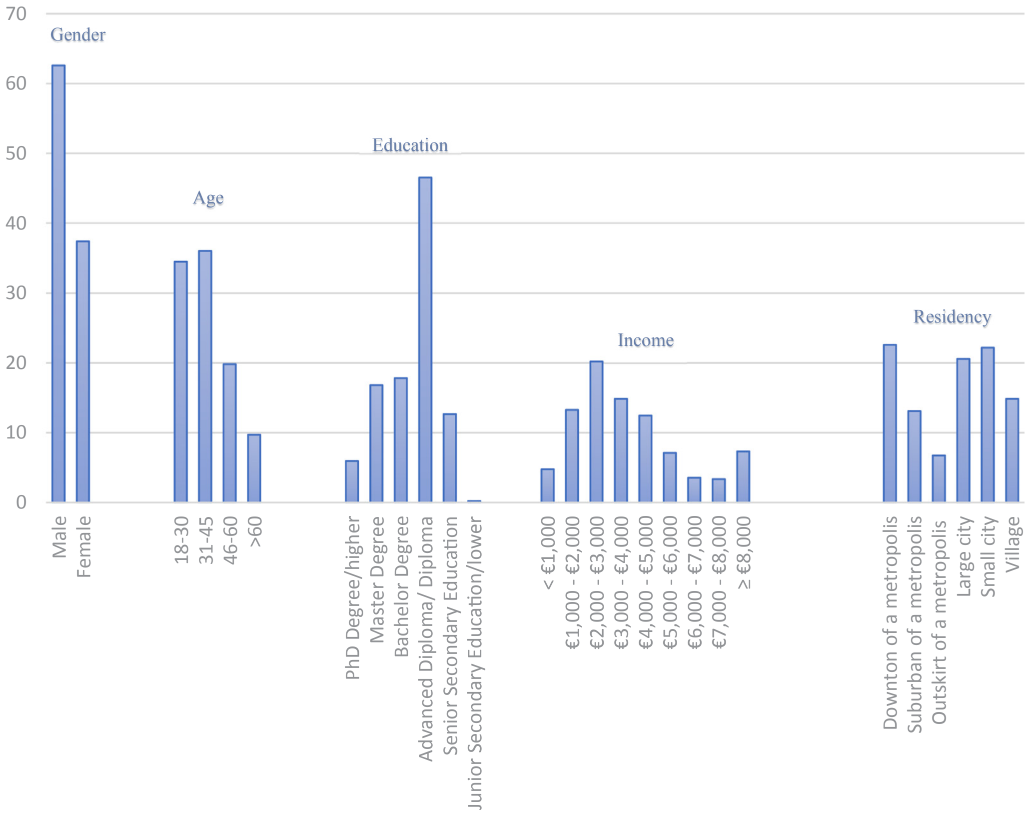


Fig. 2. Socio-demographic characteristics of the respondents.

Fig. 3. Individual mobility behaviour.

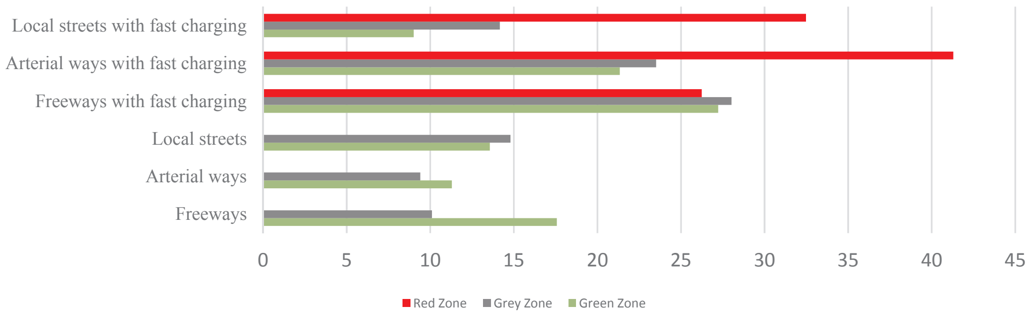


Fig. 4. Choice sets analysis.

and the availability of slow charger are included as context variables of each choice experiment as shown above in Fig. 1. β_{im} is a vector of coefficients that indicates the importance of the instrumental variable x_m corresponding to alternative i. The second term pertains to the factors that are related to the individuals including gender and age. β_{ik} is vector of coefficients that implies the importance of socio-economic variable x_k incorporated into the utlity function of alternative i.

The error term, the last component in the utility function, represents unexplained variation. MNL is the simplest logit model with ignoring all covariances (McFadden, 1974; Ortúzar and Willumsen, 2011). It hypothesizes that the random variables are independently and identically distributed (IID) following Extreme Value type 1. Therefore, it neglects the taste heterogeneity amongst individuals as well as the correlation between choices made by the same individual across time. In order to overcome these limitations, more complex models with higher degrees of freedom have been estimated. Using the software package PythonBiogeme (Bierlaire, 2003), we estimated a mixed logit model with panel effects resulted in the best model fit.

7. Results

Table 4 shows the results of the maximum likelihood estimation of the mixed logit model with considering the panel effects and 1000 Halton draws. The total number of observations and estimated coefficients are 6060 and 22, respectively. Model estimation parameters including rho-square and final log likelihood are summarised in Table 4. We have concluded that the signs of all estimated

Table 4
Results of the mixed logit model.

Name	Value	Robust Std err	Robust *t*-test
Alternative Specific Coefficients			
ASC_FREEWAY_C	4.85	0.717	6.77
ASC_ARTERIAL WAY_C	4.80	0.659	7.29
ASC_LOCAL STREET_C	3.67	0.584	6.28
Estimated Marginal Value of Parameters			
B_TT	−0.0310	0.00644	−4.81
B_TC	−0.178	0.0417	−4.27
B_CT	−0.0818	0.0225	−3.63
B_WT	−0.0271	0.0102	−2.65
B_SOC_C	−0.0345	0.00462	−7.48
B_CP_C	−0.365	0.0821	−4.44
B_E1_FREEWAY	0.120	0.0939	1.28
B_E2_LOCALSTREET	0.225	0.112	2.00
B_E3_ARTERIAL WAY	0.568	0.120	4.73
B_GENDER_W/C	−0.849	0.213	−3.99
B_AGE_W/C	0.0233	0.00724	3.22
B_INCOME_W/C	−0.140	0.0474	−2.96
B_EDUCTATION_W/C	−0.663	0.207	−3.20
Standard Deviation of Random Parameters			
SIGMA_FREEWAY_C	1.03	0.156	6.59
SIGMA_ARTERIAL WAY_C	0.922	0.109	8.48
SIGMA_LOCAL STREET_C	0.887	0.139	6.39
SIGMA_CT	0.171	0.0118	14.43
SIGMA_TC	0.316	0.0502	6.31
SIGMA_TT	−0.104	0.00655	−15.93
Model Specifications			
Number of observations	6060		
Number of estimated parameters	22		
Number of Halton draws	1000		
Final log likelihood	−8163.21		
Rho-square	0.186		

coefficients are according to expectation.

Each parameter has been labelled by a prefix and a suffix in order to enable readers to grasp the type of the estimated parameter and the associated utility function. As prefix, B, indicates the estimated marginal value of a parameter while SIGMA represents the standard deviation of a random parameter. On the other hand, the suffix W/C and C show that the corresponding exploratory variables pertain to the routes without and with fast charging, respectively. Furthermore, when a parameter ends with a road category such as freeway, arterial ways, and local streets, it represents the associated utility function in which the variable has been incorporated.

The coefficients of Alternative Specific Characteristics (ASCs) are significant and positive. They are included in the routes with fast charging, so the positive sign supports the existence of unobserved preferences towards routes with fast charging. This tendency might be due to various attitudinal factors such as range anxiety, trust in electric travelling, and so on. Furthermore, the significant SIGMAs represent the heterogeneity amongst observed as well as unobserved utility.

Unsurprisingly, travel time (B_TT) and travel cost (B_TC) as being classic route attributes have a negative effect on the utility of all route alternatives. It means that users prefer routes with lower travel time and cost. However, the marginal utility of travel cost (-0.178) is more negative than that of the travel time utility (-0.031) indicating that travellers are likely more sensitive towards cost than time. Furthermore, Value of Travel Time Saving (VTTS) which is a concept indicating the willingness of travellers to pay for a unite of travel time saving (Jara-Diaz, 2007) is estimated at 10.45 Euros/h in this research. This value which is derived by dividing the marginal value of travel time by the marginal value of travel cost is in line with the estimated VTTS in other research conducted in the Netherlands (Homem et al., 2019; Yap et al., 2016).

In the case of fast charging, the charging time (B_CT) and waiting time (B_WT) coefficients add to the disutility of the associated routes. In general, any stop for recharging or refuelling a car during a commuting trip is not desirable.

A significant different charging behaviour can be observed based on the available battery power at the origin which is the main difference between the three designed experiments. Having a negative sign, SOC at the origin can be a crucial determinant to select a route with/without fast charging. Given that initial SOC has been incorporated into the utility functions of routes with fast charging as a context variable, the higher the SOC at the origin, the higher the probability of choosing a route without fast charging.

We examined the route choice behaviour of BEV drivers in terms of selecting one of the road categories (freeway, arterial way, local street) within the designed experiments. Experiment design is intrinsic to the interaction of SOC at the origin and the electricity consumption (SOC at the destination). In the green zone where SOC at the destination (without fast charging) is higher than 50%, freeways are preferred (0.120) although it is not significant at the 95% level. Local streets appear to be favoured by travellers who end up with running out of battery power in the grey zone (0.225). This cautious behaviour may be due to the tendency of selecting a route with the lowest consumption in the case of no fast charging, therefore, yielding a greater residual SOC at the destination. In the red zone in which users must recharge their car during the trip, they may tend to select arterial ways (0.568). Arterial ways are assumed to have lower consumption than freeways and lower travel time than local streets, so travellers may select them in order to ensure that they can arrive at a fast charging point while total travel time including route travel time and charging time is taken into account.

The negative marginal value of B_CP shows that the availability of a slow charging point at the destination is a significant factor to selecting a route without fast charging. This is because when a charging opportunity is provided at the destination, drivers may feel more comfortable to perform their trip without fast charging.

Socio-demographic characteristics of the drivers included in the utility function of the routes without fast charging appear to be important to explain their choices. The gender coefficient has a negative value of -0.849 which is the most effective factor amongst other SDC variables. It suggests that female drivers are more likely to select routes with fast charging probably owing to their higher sensitivity to the battery power level than men. Age has an inverse relationship with selecting routes with fast charging so older people might prefer slow charging. This could be due to a lower trust in fast charging which can be supported by several remarks received in this survey from mostly older drivers stating that fast charging might be harmful to the battery health.

Since fast charging is more expensive than slow charging, drivers' income level is expected to be a significant parameter. Results show that a person with higher income tends to choose the routes with fast charging. Furthermore, individuals with a higher education level have a tendency towards routes with fast charging.

8. Conclusions

This study intends to demonstrate the impact of electric driving on the route choice and charging behaviour of BEV drivers. Collecting the data of 505 respondents through an SP survey, we estimated a mixed logit model expressing the underlying factors in the BEV drivers' decisions. The results suggest that the BEV drivers' route and charging preferences are dependent on the route attributes, vehicle-related variables, charging characteristics, and socio-economic factors.

Classic route attributes including route travel time and travel cost as well as fast charging-related variables such as charging time and waiting time are significant determinants in that any increase in their value on a specific route leads to a negative effect on the selection of that route.

According to the estimation results, a higher SOC at the origin can stimulate drivers to select a route without fast charging. This is because the high level of initial SOC gives more confidence to the driver in order to make the trip without fast charging. On the other hand, routes without fast charging might be preferred if a slow charging opportunity is provided at the destination next to the workplace of the respondent. Therefore, developing a trip planner application which is able to estimate the electricity consumption in different routes between a pair of OD and also show the availability of slow charging points at the destination could be a promising tool helping EV users to select an efficient route and charging method.

Local streets are preferred over freeways and arterial ways when SOC at the destination is estimated to be zero. This is because we assumed the local streets having the lowest consumption level compared to the other streets. Thus, drivers have a tendency to select a route with the lowest consumption even with the highest travel time to ensure that they can arrive at either a fast charging point in the case of charging during the trip or a slow charging point at the destination when a route without fast charging is selected. Whereas arterial ways with intermediate fast charge are favoured when charging is really necessary in order to arrive at the destination. This is because arterial ways stand between freeways and local streets in terms of travel time and consumption level which might be valued equivalently by travellers in this scenario.

Our findings underpin the implications of socio-economic characteristics. Young female drivers with a higher level of income and education are the ones who favour routes with fast charging. This could be further explained by exploring the attitudinal factors of this social group.

Similar to other studies, some limitations can be noted. Since the number of BEV drivers is relatively low, we involved HEV, PHEV, and BEV drivers in this research. While we know that BEV drivers would have had more realistic stated behaviour. Therefore, the target group can be limited to the BEV drivers for further research. Furthermore, we fixed travel purpose and trip distance which can be varied as well in future studies.

CRediT authorship contribution statement

Peyman Ashkrof: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Gonçalo Homem de Almeida Correia:** Funding acquisition, Conceptualization, Project administration, Supervision, Writing - review & editing. **Bart van Arem:** Conceptualization, Supervision, Writing - review & editing.

Acknowledgement

This research is part of the Electric Travelling project which has received funding from the ERA-NET COFUND Electric Mobility Europe (EMEurope).

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