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Modeling the charging and route choice behavior of BEV drivers

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ABSTRACT

Due to the limited cruising range of battery electric vehicle (BEV), BEV drivers show obvious difference in travel behavior from gasoline vehicle (GV) drivers. To analyze BEV drivers' charging and route choice behaviors, and extract the differences between BEV and GV drivers' travel behavior, two multinomial logit-based and two nested logit-based models are proposed in this study based on a stated preference survey. The nested structure consists of two levels: the upper level represents the charging decision, and the lower level shows the route choices corresponding to the charging and no-charging situations respectively. The estimated results demonstrate that the nested structure is more appropriate than the multinomial structure. Meanwhile, it is observed that the initial state of charge (SOC) at origin of BEV is the most important factor that affects the decision of charging or not, and the SOC at destination becomes an important impact factor affecting BEV drivers' route choice behavior. As for the route choice behavior when BEV has charging demand, the charging station attributes such as charging time and charging station's location have significant influences on BEV drivers' decision-making process. The results also show that BEV drivers incline to choose the routes with charging station having less charging time, being closer to origin and consistent with travel direction. Finally, based on the proposed models, a series of numerical analysis has been conducted to verify the effect of range anxiety on BEV charging and route choice behavior and to reveal the variation of comfortable initial SOC at origin with travel distance. Meanwhile, the effects of charging time and distance from origin to charging station also have been discussed.

1. Introduction

Concerns over petroleum dependence, energy security and environmental quality of cities caused by the large increase in gasoline and diesel powered vehicles have led to the motivation of researching on vehicles with alternative energy sources (Inês et al., 2011; Hamu et al., 2013). Due to less-pollution during use, low noise and high energy efficiency, battery electric vehicle (BEV) has attracted more and more attention of researchers, policy-makers, consumers, and industry (Jung and Jayakrishnan, 2012).

With innovations in battery technologies and support of government policies, electric vehicle has been transformed from concept into reality. In China, the government recently announced its strategic plan of promoting electricity as a replacement alternative to petroleum for transportation purposes. In Beijing, an official BEV-related development goal to have more than

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170 thousand BEVs and 10 thousand charging spots by 2017 has been published, and a variety of fiscal and institutional policies have also been proposed and implemented by the national and local governments to encourage the construction of electricity-charging infrastructures and the residents' purchase of BEV. In general, BEV has stepped into people's daily life gradually.

It is noted that BEV's cruising range confined by the battery capacity is still less than gasoline vehicle's (GV) (Woodjack et al., 2012). For example, the cruising range of a BAIC E150 is about 75 miles under actual traffic conditions, and a BYD Qin of its 2014 version can run up to 120 miles with full charge. But for one GV with 40–50 L fuel, its cruising range could be more than 310 miles. The worry of batteries running out of power en route, normally referred to as range anxiety in the literature (see, e.g., Pearre et al., 2011), inevitably affects BEV drivers' travel choices such as charging decision-making, charging station choice and route choice.

So far, there are three kinds of charge mode, including fast charging, slow charging and battery swapping. Due to non-uniform standard of battery specifications and ownership of battery, there is difficulty in constructing battery swapping station. Slow charging and fast charging is carried out in accordance with charging time. Particularly, the time spent in slow charging and fast charging are about 6–8 h and half an hour, respectively (Botsford and Szczepanek, 2009). Obviously, slow charging is more suitable for long time stay locations, such as residential areas and office areas during night or working time. However, because of forgetting to charge or having been used, the state of charge (SOC) of BEV is not always 100% before starting travel, which joints with the relative short cruising range usually cause a higher possibility of charging during travel to complete the entire trips. In these situations, the fast charging, even harmful to battery, is needed to satisfy the charging demand. This behavior is similar to that of a conventional gasoline vehicle user who can refuel the vehicle at any gas stations and any time (Bae and Kwasinski, 2012). However, compared to the refuel behavior of GV, the charging behavior of BEV drivers during travel occurs more frequently and needs more time. Therefore, BEV drivers' travel behavior modeling is different from GV drivers', specifically in the case when charging behavior occurred during travel. Obviously, the charging decision-making and charging station choice are not existed in GV drivers' travel behavior modeling.

Particularly, the main differences as regards to route choice modeling between BEV and GV drivers are shown as follows:

(1) *Variables*: The route choice variables included in traditional route choice models for GV drivers usually are limited to some basic level of service (LOS) attributes of the alternative routes, such as travel time, fare, road grade and route direction (de Dios Ortuzar and Willumsen, 2011; Raveau et al., 2011). In addition to the above mentioned attributes, the vehicle variables (e.g. SOC of BEV, energy consumption, etc.) also have important impacts on BEV route choice. Particularly, the service level and location of charging station cannot be ignored when there is a charging demand. Therefore, how to quantify the above variables and analyze their impacts on the BEV route choice become new challenges for route choice modeling.
(2) *Route choice set*: In traditional GV drivers' route choice modeling, the alternative routes have been put in the same choice set. However, the alternative routes of BEV drivers can be easily classified into two categories: routes without charging and routes with charging. Therefore, whether it is appropriate to determine the route choice set in accordance with traditional process, and then how to establish the approach to determine the rational route choice set for BEV drivers route choice modeling are highly worthy to be analyzed.

This paper is devoted to analyzing BEV drivers' charging and route choice behavior based on discrete choice model, with the additional consideration of the influences imposed by service level of charging station and vehicle variables of BEV. In order to explicitly capture the variances between BEV drivers and GV drivers on route choice modeling, four different models, which describe the charging and route choice behavior of BEV drivers, are proposed and estimated by using the stated preference (SP) survey data in Beijing, China. Through the comparison of estimated results, the proposed models' ability in explaining and predicting charging and route choice process of BEV drivers is evaluated.

The remaining part of this paper is organized as follows. The relevant literature is reviewed in Section 2. Section 3 describes the modeling methodologies and model specifications. In Section 4, the empirical results of the models and the effects of the explanatory variables are presented. The final section provides a summary of the research findings, and identifies possible extensions of the research.

2. Literature review

Travel choice behavior of GV drivers has been extensively studied in past decades, and many researches on destination, mode and route choices are reported (Florian and Nguyen, 1978; Wilson, 1989; Forinash and Koppelman, 1993; Bhat, 1997; Yao and Morikawa, 2005).

Compared to the GV drivers, the specific behavior of BEV drivers is charging behavior. Most recently, the charging behavior could be classified to two categories, i.e. fixed charging behavior and flexible charging behavior respectively. The fixed charging behavior occurs at a fixed charging location and fixed charging time during the off-peak hours for anticipating electric vehicle charging demand (Bae and Kwasinski, 2012). This behavior has been modeled in most of previous studies (Zhang et al., 2011; Hodge et al., 2010; Khan and Kockelman, 2012; Sundström and Binding, 2010; Nicholas et al., 2013). According to the studies, the fixed charging behavior has very little influences on the travel behavior of BEV drivers, so that it has been left out of our study. The flexible charging behavior, which is recharge behavior during travel, usually occurs at specific locations and adopts fast charging mode. Nicholas et al. (2012) investigated the fast charging behavior by simulating the electric vehicle travel and public fast charging. The results show that between 8.5% and 3.4% of tours would require some public charging under different range and charging assumptions, while accounting for 46% and 30% of vehicle miles traveled (VMT) respectively. Furthermore, Tal et al. (2014) focused on the charging behavior impacts on electric VMT. The data source of this study is based on a survey conducted in California and the results show that higher electric range plug-in hybrid vehicles (PHEV) drivers and BEV drivers charge more often and report more charging opportunities, while the smaller battery PHEVs in the same areas could not find chargers because of public charging availability. These studies illuminate the flexible charging behavior exist in real word, but they didn't analyze the influences caused by charging behavior on travel behavior, especially route choice behavior.

Extensive research has been carried out in the area of route choice. Previous research has established theories and models of route choice decision-making process and has identified route choice factors besides of the traditional variables, such as travel time and distance. Multinomial logit (MNL) model, in which very strict assumption of independence of irrelevant alternatives (IIA) is needed, has been widely applied to the analysis of route choice behavior during past decades. Several modifications or generalizations of the logit structure (e.g., C-logit, path-size logit (PSL), cross-nested logit (CNL)) have been proposed to relax the IID assumptions of the error term of MNL model, and these models have been widely used in many studies (Pillat et al., 2011; Hood et al., 2011; Broach et al., 2012; Train, 2001; Koppelman and Wen, 2000).

The route choice factors usually include route attributes, individual characteristics, traffic information, and travel characteristics. The studies conducted by Arentze et al. (2012) indicated that road accessibility characteristics have a substantial impact on route preferences which is of the same order of magnitude as variation in travel times. Raveau et al. (2011) defined the angular cost variable to reflect the directness of the chosen route, and found it is helpful to improve the explanation of route choices. Matsumoto et al. (2008) emphasized on the traffic information, and found that the increasing or decreasing 10 min of travel time has influences on 80% of drivers. Tawfik et al. (2010) considered the heterogeneity of drivers, and found that drivers' route choice evolution is not identical.

As regards BEV, the previous researches have been mostly on BEV purchases. The discrete choice models have been widely used to predict consumer's BEV purchase decision (Al-Alawi and Bradley, 2013). The battery range limitation, high cost, and the charging infrastructure are the most significant factors on consumers purchase decision (Neubauer et al., 2012; Egbue and Long, 2012; Carley et al., 2013; Sierzchula et al., 2014; Dong et al., 2014). However, there are not further researches on the BEV-use behavior (namely BEV travel behavior) in these studies. For the existing of flexible charging behavior, the BEV drivers' route choice behavior is different from the traditional travel route choice behavior. As mentioned above, besides of level of service (LOS) attributes of the alternative routes, the fast charging infrastructure information and vehicle information, especially the SOC of BEV and energy consumption of route, also should been introduced into route choice factors. There are several studies focusing on the BEV flow assignment in road network. Jiang et al. (2012, 2014) presented a mathematical programming model and solution method for the path-constrained traffic assignment problem, in which route choices simultaneously follow the Wardropian equilibrium principle and yield the distance constraint imposed on the path. Zhang et al. (2013a) has discussed the impacts of electric-charging price on network flows of BEV based on the assumption that the charging behavior occurred at origin or destination. Based on a simplified PEV drivers' route choice behavior, Gardner et al. (2013) proposed a PEV traffic assignment to quantify the relationship between the travel patterns of PEV drivers and PEV energy consumption rates, in which PEV driver is assumed to behave in the same manner as non-PEV drivers, particularly in regard to route choice. Zhang et al. (2013b) proposed a NL structure to describe the travelers' departure time, duration of stay and route choices, based on the assumption that BEV drivers recharge the vehicle at destination. In the problem that optimal deployment of public charging stations for plug-in hybrid electric vehicles, He et al. (2013a) proposed a combined distribution and assignment model to describe PHEVs' choices of destinations and routes based on assuming charging at each destination. Jiang and Xie (2014) offered a traffic equilibrium modeling tool for networks that serve households/motorists who can choose between gasoline and electric vehicles. Agrawal et al. (2015) developed a model based on the shortest path problem with non-additive costs and introduced a random variable denoting the disutility from running out of range to accommodate differences in drivers' risk attitudes towards range. However, the above studies did not consider the charging behavior during travel and its influences on route choice behavior, while the proposed models in above studies are just theoretical without demonstration. Furthermore, He et al. (2013b) described a charging behavior based on electrify roads by envisioning wireless power transfer technology to recharge electric vehicle, but there is no evidence to demonstrate that this technology will be applied in China in the near future. With different considerations of BEVs' energy consumption and recharging time during travel, He et al. (2014) proposed three mathematical models and solution algorithms to describe the resulting network equilibrium flow distributions on regional or metropolitan road networks. But the BEV drivers' travel behavior is assumed to select the route with minimize their trip times or costs while making sure to complete their trips without running out of charge.

In conclusion, the existed researches have few considerations on the flexible charging behavior of BEV drivers and its influences on route choice behavior, while mainly focused on the traffic flow assignment of BEVs. Therefore, aiming to analyze the charging and route choice behavior of BEV drivers, identify the main affecting factor on the decision of charging, route choice, and reveal the preference of charging station selection, a logit-based modeling framework considering the joint charging and route choice is proposed in this paper.

3. Choice modeling

3.1. Explanatory variables

There are four categories of explanatory variables that influence BEV drivers' charging and route choice propensity, including individual characteristics, route attributes, vehicle variables, and charging station attributes. The individual characteristics and route attributes as the standard explanatory variables are incorporated in traditional models. The choice of variables for potential inclusion in the model is guided by previous theoretical and empirical work on choice modeling. The final specification is based on a systematic process of eliminating variables, which found not to be statistically significant or the sign is contrary to logic in previous specifications, and based on considerations of parsimony in representation.

The individual characteristics are designed to account for the preference variations in choices between different population groups. This group of variables includes driver's gender, occupation, income, and education level. Since the respondents have complete information of routes in SP survey, the drivers' characteristics are suitable to distinguish population groups which have different risk attitude for charging and route choice.

The route attributes tries to capture the impact of the routes' LOS on drivers' decision making. The travel time and travel cost from origin to destination as the standard explanatory variables are designed to describe the quickness and economy for each route alternative. To reflect drivers' preference of high level road, the total ratio of express way and arterial way is also integrated into the model. Given that drivers prefer the most direct routes from origin to destination, the angular cost variable defined by Raveau et al. (2011) is added to represent routes' directionality.

Considering the characteristics of BEV, the vehicle variables have significant impact on drivers' charging and route choice behavior. Three variables are adopted in this paper, including initial SOC at origin, average electric consumption factor, and SOC at destination. The *initial SOC* at origin is a crucial reference to evaluate the cruising range of BEV before travel. The *average electric consumption factor* (*AEC*), which represents the average electric consumption for the whole route, a model is proposed to calculate the variable by introducing the vehicle specific power (VSP) (Jimenez-Palacios, 1998). *VSP*, which is defined as the instantaneous power per unit mass of the vehicle, is used as an intermediate variable in the modeling of energy consumption for the function of reflecting the influence of microscopic driving parameters. The following simplified function Eq. (1) is used to estimate the *VSP* for light-duty vehicle.

$$VSP = v \times (1.1 \times a + 0.132) + 0.000302 \times v^3 \tag{1}$$

where v and a are the instantaneous speed and acceleration of the vehicle in m/s and m/s^2 respectively.

The detailed model process is shown as follows.

First, since the characteristics of BEV energy consumption change under different travel conditions, *VSP* is separated as a bin with an equal interval of 1kw/t. Specially, *VSP* = 0 is set as a single range because the size of the sample is relatively large when *VSP* = 0, as described in Eq. (2).

$$VSP\ bin = \begin{cases} n, & \forall VSP \in [n, n+1),\ (n = -30, -29, \ldots, -1) \\ 0, & VSP = 0 \\ n, & \forall VSP \in (n-1, n],\ (n = 1, 2, \ldots, 30) \end{cases} \tag{2}$$

Each *VSP* bin is associated with an average energy consumption rate, which is defined as the energy consumption per unit time. The second-by-second data collected by a chassis dynamometer test of Foton BEV according to New European Driving Cycle (NEDC) which is supposed to represent the typical usage of a car in China and Europe, is divided into traveling fragments by 60 s intervals and each fragment is characterized with its average speed. The average speed of EV is divided into different bins by the step of 3.6 km/h, and then the VSP-Bin distributions under different average speed bins are obtained. The average energy consumption rate under each average speed bin is estimated by:

$$\overline{ER}_i = \sum_j ER_j \cdot D_{ij} \tag{3}$$

where $\overline{ER}_i$ is the average energy consumption rate for the ith average speed bin; ER_j is the energy consumption rate for the jth VSP-Bin; D_{ij} is the VSP-Bin distribution for the ith average speed bin and the jth VSP-Bin.

Then the energy consumption factor, which is defined as the energy consumption per unit distance, under each average speed bin is estimated by:

$$V_i = \sum_{k=1}^{n} D_{ik} \Bigg/ \sum_{k=1}^{n} T_{ik} \tag{4}$$

$$EF_i = \overline{ER}_i \cdot \sum_{k=1}^{n} T_{ik} \Bigg/ \sum_{k=1}^{n} D_{ik} \tag{5}$$

where T_{ik} is the travel time of EVs spent in the kth segment of the ith average speed bin, h; D_{ik} is the mileage of EVs during the kth segment of the ith average speed bin, km; V_i is the average speed of the ith average speed bin, km/h; EF_i is the energy consumption factor, kwh/km; n is the number of driving segments.

Referring to the expression form designed to link energy consumption factor and average speed of GVs (Yao and Song, 2013), the parameters of model are estimated by regression analysis method based on the results calculated from Eqs. (4) and (5):

$$EF = 1.359/v - 0.003 \cdot v + 2.981 \times 10^{-5} \cdot v^2 + 0.218 \quad (6)$$

where EF is the energy consumption factor, kwh/km; v is the average speed of BEV, km/h.

Further, the output voltage of power battery, which has observed very little variations in travel process, is approximately regarded as a constant. Therefore, the electric consumption is calculated by Eq. (7).

$$EC = EF/U = 3.576/v - 7.895 \times 10^{-3} \cdot v + 7.845 \times 10^{-5} \cdot v^2 + 0.574 \quad (7)$$

where EC is the electric consumption factor, A h/km, which is a function of average speed v; U is the output voltage of power battery, V. U is determined to be 380 V in this paper based on observation of modeling data.

Finally, the AEC, which is the average value of energy consumption factor for the whole route, is calculated by,

$$AEC = \sum_i \frac{l_i}{L} EC(v_i) \quad (8)$$

where l_i is length of the ith link of the route, m. L is the length of the route, m. v_i is the average speed of the ith link.

As regards *SOC at destination*, which is affected by initial SOC and electric consumption during travel, is used as an indicator reflecting the impact of drivers' range anxiety on charging and route choice. That is, the higher SOC BEV has at destination, the less range anxiety the driver feels during travel. And the value of SOC at destination can be calculated by,

$$SOC_d = SOC_0 - \frac{AEC \cdot L}{Q} \times 100\% \quad (9)$$

where SOC_d is the SOC at destination, %. SOC_0 is the initial SOC at origin, %. Q is the battery capacity of BEV, A h.

Obviously, when any two variables among three vehicle variables are determined, another one can be easily calculated by Eq. (9). Therefore, only two vehicle variables can be adopted into model.

The variables concerning charging station attributes are designed to capture the impact of the service level and the location of charging station on route choice with charging. Based on the assumption that charging cost rates are unique in different charging stations, the LOS attribute of charging station is only *charging time*, which is the sum of waiting time and charging service time. As regards the location of charging station, two variables reflecting factors related to the *angular formed by origin*, *charging station, and destination* (hereafter referred to as AOCD, an example in Fig. 1) and *the distance from origin to charging station* are also integrated into the model.

3.2. Description of the model

The choice model in this paper is a logit-based design in which the user utility function contains the standard explanatory variables representing route attributes plus additional ones for vehicle variables and charging station attributes.

Compared to GV drivers', BEV drivers' route choice behavior is significantly influenced by charging behavior when charging is needed. According to whether detouring to charge, the BEV drivers' route choice set could be classified into two categories: routes without charging and routes with charging. Considering the difference in variances of unobserved component between these two categories, a NL formulation is more appropriate than MNL to describe the choice situation. In order to reflect the difference between BEV drivers and GV drivers, four different logit models are proposed to describe the charging and route choice behavior of BEV:

Both M1 and M2 are multinomial logit (MNL) formulations. M1 containing only traditional service level variables (that is, without vehicle variables and charging station attributes) is used for comparison purpose. M2 is an extended model with three categories variables, namely route attributes, vehicle variables and charging station attributes. As for each scenarios (namely each combination of the OD pair ad the initial SOC level), the *initial SOC at origin* has no difference among alternatives. Therefore, *AEC* and *the SOC at destination* are involved into the utility function of M2 to respectively represent the electric consumption during travel and the impact of drivers' range anxiety.

M3 and M4 are proposed based on nested structure shown in Fig. 2. The upper level indicates the decision of charging or not. The lower level shows the route choice combinations for no-charging and charging. Furthermore, to overcome the overlapping problem in applying the MNL, a PSL structure is applied to route choice without charging in lower level. The correction term of PSL is given by Eq. (10).

$$PS_k^{rs} = \sum_{a \in \Gamma_k} \frac{l_a}{L_k^{rs}} \frac{1}{\sum_{j \in K_{rs}} \delta_{aj}^{rs}} \quad (10)$$

where l_a is the length of link a; L_k^{rs} is the length of route k between O–D pair rs; δ_{aj}^{rs} is equal to 1 for link a on route k between O–D pair rs and 0 otherwise.

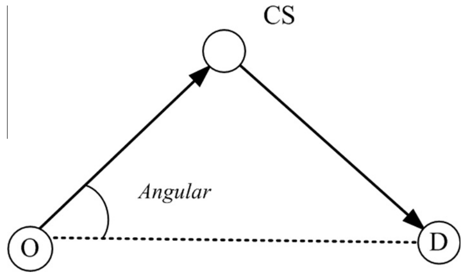


Fig. 1. Diagram of angular formed by origin, charging station, and destination.

However, a MNL structure is applied to route choice with charging in lower level, since the routes with different charging stations usually have less overlapped links and are regarded as different route choice alternatives, which meet the IIA assumption. Compared to M1 and M2, initial SOC at origin are more intuitive than AEC to reflect the impacts on the decision of charging or not by vehicle variables, therefore initial SOC are involved in the M3 and M4. And compared to M3, the individual characteristics are added in the utility function of M4. The correlation among these models is shown in Fig. 3.

4. Data

The empirical case deals with charging and route choice of BEV drivers. Due to the limited cruising range, BEV drivers' travel behavior is significantly different from GV drivers', specifically in the case when charging behavior occurred during travel. Therefore, to explicitly capture the characteristics in BEV drivers' charging and route choice behavior, a SP survey was designed and implemented in the Beijing, China from February to June, 2014. Given that it is difficult to collect enough samples if the respondents are restricted to BEV drivers strictly, the respondents in this survey are common drivers. In order to ensure the respondents' preference extracted from the questionnaire survey conforms to the reality, all respondents are assumed to own a BEV, which is in accordance with the vehicle type of energy consumption data collection test.

At the beginning of survey, some basic information about EV, such energy consumption characteristics, cruising range, etc. is revealed to the respondents, e.g.,

(1) *BEV's cruising range*

The lower the initial SOC at origin is, the lower the cruising range is. The lower the initial SOC at origin is, the faster the cruising range decreases (see Table 1).

(2) *Correlation of the electric consumption factor and average travel speed*

As shown in Fig. 4, the eco-speed is from 35 km/h to 75 km/h.

(3) *Precautions for driving BEV*

When the SOC is lower than 30%, the cruising range of BEV is only about 9 miles, and the rate of electric consumption is increased significantly. When the SOC is lower than 10%, caused by the no-eco driving behavior (e.g., sudden stop and fast move), there exists the risk of "vehicle abrupt flameout".

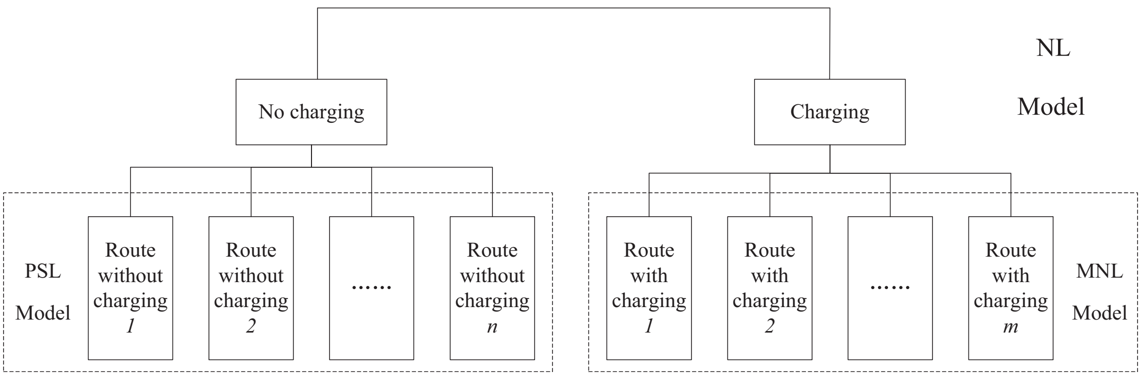


Fig. 2. NL model structure of BEV drivers' charging and route choice.

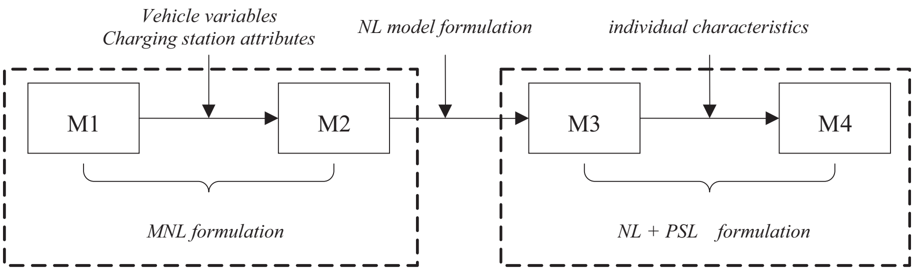


Fig. 3. Correlations among M1, M2, M3 and M4.

Table 1
The BEV's cruising range with different SOC level.

SOC level	100%	70%	50%	40%
BEV's cruising range	About 75 miles	About 44 miles	About 25 miles	About 19 miles

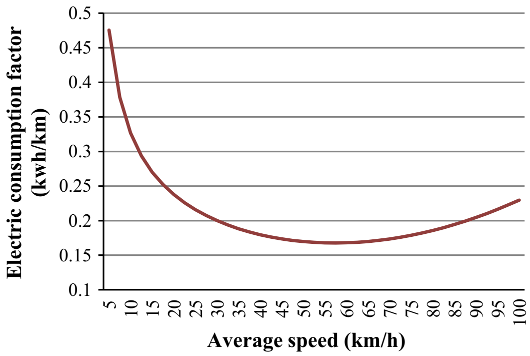


Fig. 4. The curve of electric consumption factor with average speed.

Then, by selecting four origin-destination (OD) pairs and dividing the initial SOC into three levels, all respondents in the SP survey were given 12 route choice scenarios to make decision, as shown in Table 2. And all destinations are assumed to have charging infrastructure to refuel BEV. In each scenario, the origin, the destination, the charging station, three routes without charging and three routes with charging are displayed for respondents by diagrammatic sketch. The routes without charging of each OD pair are favorite routes based on a preliminary investigation, and the routes with charging are generated from the above routes according to the location of charging stations. An example of the diagrammatic sketch is shown in Fig. 5. Furthermore, the alternatives of routes without charging involve route attributes (e.g., travel distance, travel time, and travel cost) and vehicle variables (e.g., initial SOC at origin, electric consumption, and SOC at destination). Besides route attributes and vehicle variables, the alternatives of routes with charging also involve charging station attributes, including the distance from origin to charging station and charging time.

Each respondent is asked to make decision for two questions in each scenario. First, the decision for whether charging or not should be made by each respondent. Then, if respondent chooses non-charging, three routes without charging are given to be chosen. Correspondingly, three routes with charging are given to be chosen, if respondent chooses charging. In total, 237 respondents constituted the sample frame for this experiment. The respondents' individual characteristics (e.g., gender, driving years, age, occupation, income, and education level), charging and route choice preferences for all the 12 scenarios are obtained in this SP survey. And the final number of observations used in the model estimation is 1404 by eliminating the invalid data.

5. Estimation results

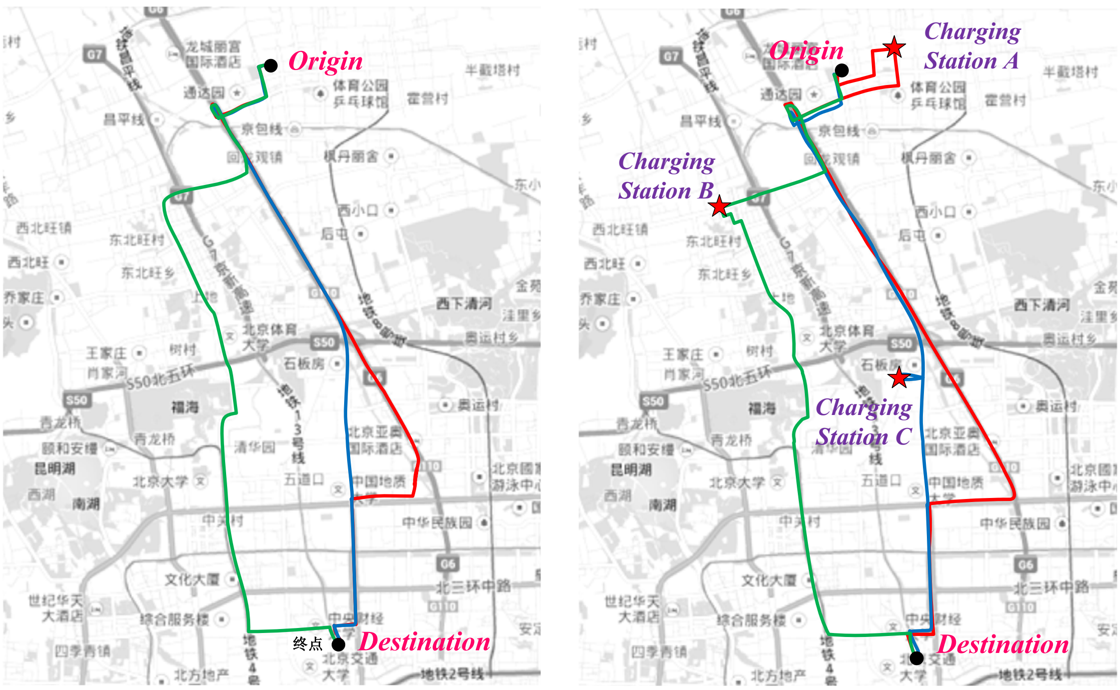
The parameters of the four models are estimated by the maximum likelihood method and the results are shown in Table 3. All of the parameters estimated for the proposed models have the right sign and most of them are statistically significant at the 95% level.

Focusing on the goodness-of-fit measures, the log-likelihood and adjusted ρ^2 statistics, demonstrate that the model (M2) with special variables (i.e. vehicle variables and charging station attributes) outperform the based model (M1). The NL

Table 2
The choice scenarios in the SP survey.

Trip type	Average trip distance	OD pair	Initial SOC	Scene ID
Long trip	About 20 km	Huilongguan → BJTU	High 70%	1
			Medium 50%	2
			Low 40%	3
		Wangjing → Xidan	High 70%	4
			Medium 50%	5
			Low 40%	6
Short trip	About 10 km	Wangjing → Sanyuanqiao	High 60%	7
			Medium 40%	8
			Low 30%	9
		BJTU → Wangfujing	High 60%	10
			Medium 40%	11
			Low 30%	12

Note: BJTU (Beijing Jiaotong University).



(a) Routes without Charging (b) Routes with Charging

Fig. 5. Example of the routes without charging and routes with CS.

formulation model (M3) outperform the MNL formulation model (M2), which indicates that such a NL formulation is appropriate for describing charging and route choice behavior of BEV drivers. Meanwhile, the comparison of M3 and the proposed final model (M4) reveals that it is helpful to explain the BEV drivers' variation in charging and route choice behavior by dividing the travelers into different groups in M4.

As for the results of M4 shown in Table 3, in addition to the logsum parameters of route choice without charging and route choice with charging, the variables in upper level including initial SOC at origin, constant and all drivers' character dummy variables are designed to explain the decision-making process of charging or not.

The initial SOC at origin as the priority variable to determine the level of range anxiety, significantly yields the positive sign conforming to the common logic that higher possibility of charging caused by lower initial SOC. Alternative specific constant for no-charging in upper lever is estimated with a negative significance indicating that drivers are inclined to charging to relax the range anxiety.

Most of the dummy variables explicitly highlight the behavioral trend on whether charging or not. In this study, the dummy variables that are considered in the upper level of NL model are driver's characteristics. The dummy variable for

Table 3
Estimation results for the NL model of BEV drivers' charging and route choice (*t-values* in parentheses).

Variable	M1	M2	M3	M4
Generic variables for route				
Travel time (minute)	−0.109 (−10.915)	−0.086 (−6.028)	−0.105 (−4.440)	−0.105 (−4.511)
Travel cost (CNY)	−0.146 (−5.739)	−0.136 (−5.010)	−0.127 (−4.029)	−0.127 (−4.031)
Total ratio of express way and arterial way (%)	0.304 (2.600)	0.580 (4.574)	0.934 (5.431)	0.930 (5.439)
Route without charging				
Angular cost	−0.107 (−4.793)	−0.340 (−9.214)	−0.286 (−3.307)	−0.287 (−3.360)
SOC at destination (%)	–	11.880 (50.507)	0.224 (3.611)	0.223 (3.641)
AEC (A h/km)	–	−4.871 (−10.261)	–	–
log(*PS*)	–	–	4.209 (3.516)	4.204 (3.515)
Route with charging				
Charging time (minute)	−0.018 (−4.641)	−0.065 (−5.754)	−0.079 (−4.059)	−0.079 (−4.120)
Distance from O to charging station (km)	–	−0.126 (−6.268)	−0.130 (−4.789)	−0.130 (−4.792)
AOCD (rad)	–	−0.299 (−3.729)	−0.388 (−3.900)	−0.387 (−3.899)
Scal parameters				
μ	–	–	0.449 (3.351)	0.468 (3.387)
No-charging				
Initial SOC at origin (%)	–	–	0.063 (1.802)	0.063 (1.827)
Constant	–	–	−10.377 (−4.743)	−11.003 (−4.708)
Charging				
Female driver	–	–	–	0.720 (2.016)
High education	–	–	–	1.530 (2.848)
High personal income	–	–	–	−1.054 (−2.010)
Occupation dummy	–	–	–	−0.747 (−1.477)
Sample size	1404	1404	1404	1404
Log-likelihood	−2438.5	−2064.4	−2036.1	−2016.6
Adjusted ρ^2	0.031	0.178	0.189	0.196

female drivers in charging utility function is significantly positive expressing that female drivers are more discreet than the others and trend to charge BEV in travel.

The education degree dummy is also incorporated in the estimated model as a dummy in no-charging utility function. When the drivers have master or doctor degree, they have higher propensity to choose charging since they are more rational and discreet than the others. From the significantly negative income dummy parameter, when driver's income is more than 10,000 China yuan (CNY) per month, he/she will not prefer to choose charging, which means that the driver with higher income has higher value of time (VOT), and prefers to no charge and take the risk of batteries running out of power en route, rather than spend time to charge.

Driver's occupation is tested as dummies introduced in charging utility function of upper level of NL model. According to the results, the driver, who worked for foreign company, private company, or himself, is inclined to take the risk of no-charging. The basic reason is that drivers who take up one of above occupations usually have higher VOT caused by higher income or more adventurous spirit than the others in China. Therefore, the result indirectly highlights the interaction between the attitude facing the risk of no-charging and the occupation.

The scale parameter of the upper level is estimated to be 0.4684, and it falls between 0 and 1 satisfying the requirements of the nest structure. The generic variables in the utility functions of route choice without charging and route choice with charging are estimated with reasonable significance. Among these variables, the related parameters of travel time and travel cost are significantly negative, and the parameter of total ratio of express way and arterial way is significantly positive. It is consistent with previous studies that drivers prefer to choose the route with less travel time, less travel cost and higher total ratio of express way and arterial way.

Based on the systematic process of eliminating variables, the coefficient for the angular cost variable is only significant as a variable in utility function of route without charging. And it is negative which is consistent with the defining in Raveau et al. (2011). This phenomenon reveals that BEV drivers pay more attention to the routes direction in route choice without charging. And the SOC at destination and AEC, reflecting the energy consumption, are also only added in the utility function of route without charging. Reason behind this is that the energy consumption is paid less attention by BEV drivers due to the fully charging on the way.

The logarithm of the path size variable estimated to be 4.204 is consistent with theory. It is significantly different from 1.0, which would be the expected value if the path-size parameter captures only the statistical error introduced by the IIA property of the MNL model. It has been suggested that the path-size parameter should not be arbitrarily fixed to 1.0, since it may have a meaningful behavioral interpretation (Frejinger and Bierlaire, 2007).

By considering the charging behavior, the charging station variables including service level variable and location variable are tested as specific variables in utility function of route with charging station. The coefficient for the charging time is significantly negative expressing the drivers' willingness of reducing the charging time. The location of charging station is reflected by the AOCD and the distance from origin to charging station in the estimated model. Among these variables, the AOCD is estimated with a negative significance expressing that driver is inclined to choose the charging station which is closed to the travel direction. And the coefficient for the distance from origin to destination is also significantly negative indicating that driver prefer to charge as soon as possible for reducing the *range anxiety* in the route choice with charging. The above phenomenon indicates that the charging station should be located close to the areas with high travel demand and the direction of OD with more traffic volume.

The VOT for the estimated model is a measure that represents the external validity of the model, and it can be calculated by using the coefficients of travel time and travel cost. According to the specification of the proposed model, the VOTs of travel time and charging time are calculated according to Eq. (11) and the results are shown in Table 4.

$$VOT = \rho_t/\rho_c \tag{11}$$

where ρ_t is the coefficient of travel time or charging time, ρ_c is the coefficient of travel cost.

Considering the lack of comparative literature about travelers' VOT in Chinese cities, the personal income was adopted as comparison (Wang, 2011). Due to most of the respondents in SP survey owning vehicle, it is reasonable that the VOTs of travel time and charging time are a little higher than the average hourly wage in Beijing (37 CNY/h). Therefore, the estimated model intuitively represents the actual circumstances in the surveyors. Note that the VOT of travel time is higher than that of charging time. It is viewed that despite the charging time is extra time for travel, the time spent in charging station is more freedom than that in vehicle and can be used for work affairs or rest.

6. Numerical analysis

6.1. Effect of range anxiety

Range anxiety, which refers to the worry of BEV's cruising range insufficient to whole route, inevitably affects drivers' charging and route choice behavior. When the travel distance is informed prior by vehicle navigation system, the cruising range perception of BEV drivers becomes the core factor to reflect the range anxiety of BEV drivers. Limitations in BEV performance and discreet attitude to risk may cause pessimistic bias for cruising range. It means that expected cruising range is less than actual cruising range. On the contrary, optimistic attitude to risk may cause optimistic bias for cruising range, so the expected cruising range is longer than actual cruising range. Therefore, there are three possibilities of the cruising range perception, i.e. no bias, pessimistic bias and optimistic bias. Considering that the cruising range can be calculated by SOC variables including initial SOC at origin and SOC at destination in choice modeling, the above biases can be described by the transformations of SOC variables. Specifically, a logarithmic form and an exponential form of SOC are applied to reflect the pessimistic attitude and optimistic attitude for cruising range respectively (Eq. (12)). The biases for these three attitudes are described in Fig. 6. Appling the transformed variables for pessimistic bias and optimistic bias instead of the

Table 4
The VOTs of travel time and charging time.

Variable	Travel time	Charging time
VOT (CNY/h)	49.8	37.4

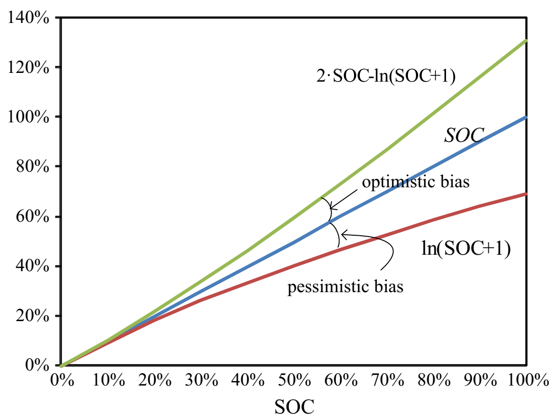


Fig. 6. Transformed SOC variables and the corresponding biases.

Table 5
Estimation results for four extra models with transformed SOC variables (*t-values* in parentheses).

Variable	M3′	M4′	M3″	M4″
Generic variables for route				
Travel time (minute)	−0.113 (−5.288)	−0.113 (−5.354)	−0.104 (−4.332)	−0.104 (−4.400)
Travel cost (CNY)	−0.124 (−3.938)	−0.124 (−3.938)	−0.127 (−4.034)	−0.127 (−4.034)
Total ratio of express way and arterial way (%)	0.880 (5.395)	0.878 (5.394)	0.941 (5.440)	0.938 (5.445)
Route without charging				
Angular cost	−0.319 (−4.130)	−0.320 (−4.179)	−0.281 (−3.214)	−0.283 (−3.266)
SOC at destination (%)				
log(SOC + 1)	0.261 (3.723)	0.260 (3.754)	–	–
2 · SOC − log(SOC + 1)	–	–	0.136 (3.610)	0.135 (3.637)
log(*PS*)	4.326 (3.624)	4.326 (3.626)	4.201 (3.504)	4.195 (3.505)
Route with charging				
Charging time (minute)	−0.084 (−4.746)	−0.085 (−4.800)	−0.078 (−3.965)	−0.078 (−4.024)
Distance from O to charging station (km)	−0.127 (−4.727)	−0.127 (−4.726)	−0.131 (−4.791)	−0.130 (−4.794)
AOCD (rad)	−0.375 (−3.827)	−0.374 (−3.822)	−0.390 (−3.906)	−0.388 (−3.904)
Scal parameters				
μ	0.502 (3.562)	0.521 (3.597)	0.442 (3.338)	0.459 (3.370)
No-charging				
Initial SOC at origin (%)				
log(SOC + 1)	0.096 (2.113)	0.096 (2.140)	–	–
2 · SOC − log(SOC + 1)	–	–	0.037 (1.770)	0.037 (1.795)
Constant	−11.236 (−5.001)	−11.803 (−4.981)	−10.174 (−4.722)	−10.811 (−4.679)
Charging				
Female driver	–	0.653 (2.067)	–	0.730 (2.011)
High education	–	1.386 (2.974)	–	1.552 (2.837)
High personal income	–	−0.954 (−2.058)	–	−1.069 (−2.005)
Occupation dummy	–	−0.679 (−1.502)	–	−0.758 (−1.473)
Sample size	1404	1404	1404	1404
Log-likelihood	−2032	−2012.25	−2037.05	−2024.2
Adjusted ρ^2	0.191	0.198	0.188	0.195

corresponding original SOC variables into the model structure of M3 and M4 respectively, four extra models (i.e. M3′, M4′, M3″ and M4″) are proposed and the estimated results are shown in Table 5.

$$\begin{aligned} &\text{Normal attitude}: \quad SOC \to SOC' = SOC \\ &\text{Pessimistic attitude}: \quad SOC \to SOC' = \ln(SOC+1) \\ &\text{Optimistic attitude}: \quad SOC \to SOC' = 2 \cdot SOC - \ln(SOC+1) \end{aligned} \tag{12}$$

Compared to M3 and M4, the pessimistic bias models (M3′ and M4′) have a better goodness-of-fit and the optimistic bias models (M3″ and M4″) have a worse goodness-of-fit. The result shows that the respondents in this survey are inclined to show pessimistic attitude to cruising range, which verifies the existence of effect from range anxiety on BEV charging and route choice behavior. Meanwhile, the above analysis reveals that accurately evaluating the BEV cruising range by deepening understanding BEV characteristics or providing accurate real-time information about traffic and BEV, is helpful to relieve range anxiety.

6.2. Comfortable initial SOC at origin

To characterize the nature of range experience and range utilization, *comfortable range* is defined by Franke et al. (2012). When the energy consumption characteristics of BEV and travel information about the routes are informed to drivers, comfortable range can be equivalent to comfortable initial SOC at origin. In this paper, the comfortable initial SOC at origin is defined as the lowest initial SOC at origin status to make the probability of no-charging greater than 50%.

To analyze the variation of comfortable initial SOC at origin in different travel, a numerical example is presented. The example is a three-node network shown in Fig. 7, including a route with charging and a route without charging. All routes pass through Node C, and route with charging need be charging at node C. Node O is origin and node D is destination. Node C is a charging station and the distance from O to C is two fifth of the distance from O to D.

Based on the M3′ model, the values of comfortable initial SOC at origin for increasing distance (from 5 km to 35 km) are given in Fig. 8. Compared to the comparison line (the dash line in Fig. 8), the slope of comfortable initial SOC values increases gradually with travel distance increasing. The reason of this phenomenon is the pessimistic attitude for cruising range, which is reflected in M3′. Furthermore, when the travel distance is zero as an extreme case, the value of comfortable initial SOC is still about 58%. This phenomenon reveals that BEV drivers have a basic value for comfortable initial SOC when using BEV for travel, no matter how long the travel distance is.

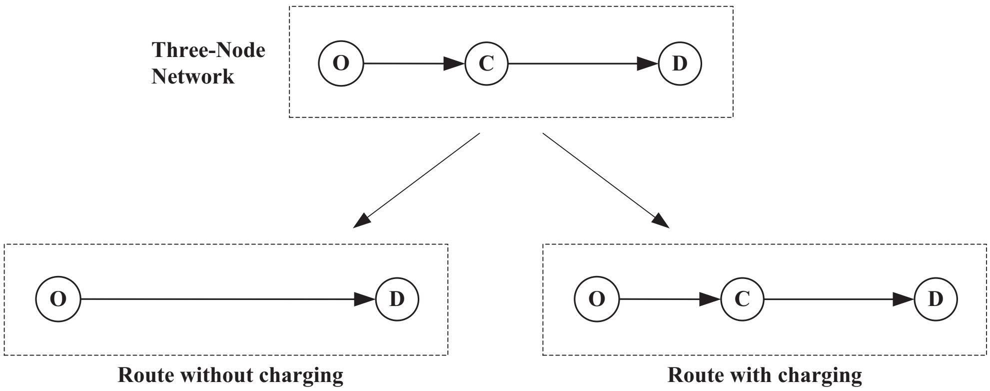


Fig. 7. Three-node network.

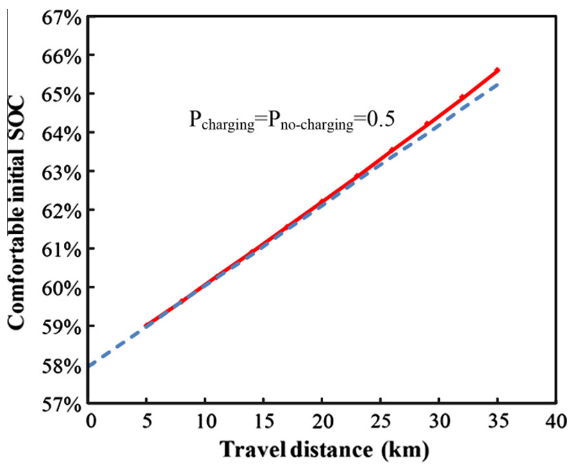


Fig. 8. Values of comfortable initial SOC with travel distance increasing.

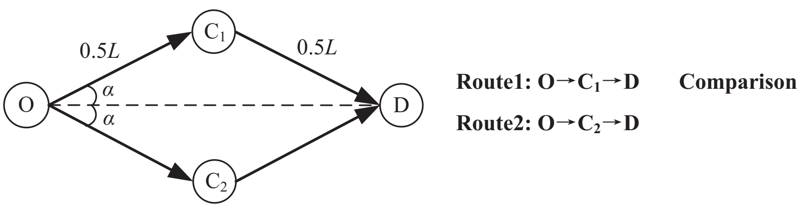


Fig. 9. Four-node network.

6.3. Effects of charging time and distance from origin to charging station

According to the above analysis in Section 4, the charging station variables, such as charging time and distance from origin to charging station, have significantly effect on the charging and route choice behavior of BEV drivers, especially on the route with charging choice behavior. A numerical example is presented to intuitively reflect the effects of charging time and distance from origin to charging station on route with charging choice. The example is a four-node network shown in Fig. 9, including two routes with charging, i.e. Route1 ($O \rightarrow C_1 \rightarrow D$) and Route2 ($O \rightarrow C_2 \rightarrow D$). Both of the routes have same route attributes, vehicle variables, and AOCD of charging station. The charging station C_1 locates in the middle of Route1 and the charging time of Route1 is 20 min.

Based on the M3′ model, the choice probabilities of Route1 and Route2, and the deviation of routes' choice probabilities (which is calculated by the choice probability of Route1 minus that of Route2), are calculated by setting the same distance from origin to charging station for Route1 and Route2, and the variation of these values with the change of charging time are summarized in Fig. 10a. And Fig. 10b shows the values and deviation of routes' choice probabilities with the change of the

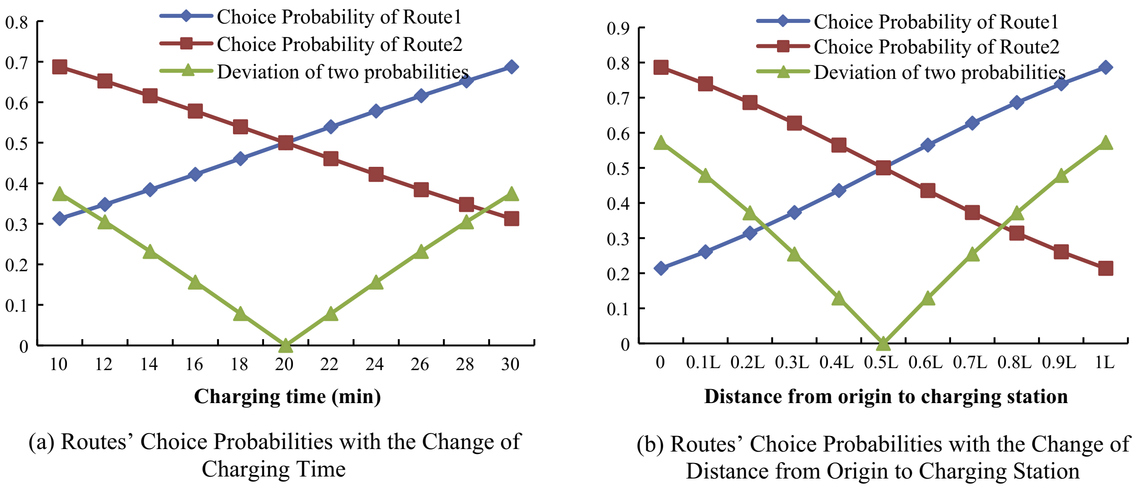


Fig. 10. Values and deviation of routes' choice probability.

distance from origin to charging station, by setting the same charging time for Route1 and Route2. We can easily find that the deviation of the probabilities is proportional to the deviation of charging time or distance from origin to charging station. This phenomenon reveals that the deviation of the charging stations' service level or location affects the choice probability of route and the utilization ratio of charging station.

Furthermore, based on the M3′, the marginal rate of substitution (*MRS*) between charging time and distance from origin to charging station is calculated by Eq. (13) and the result is 0.6 min/km.

$$MRS = \rho_{ct}/\rho_{cd} \tag{13}$$

where ρ_{ct} is the coefficient of charging time, ρ_{cd} is the coefficient of distance from origin to charging station.

The result shows that BEV drivers can endure 36 extra seconds for charging, when distance from origin to charging station is reduced 1 km. Therefore, to reduce the delay caused by charging BEV, charging station should be set in the origin of travel, e.g. residential area and working area. And the MRS between charging time and distance from origin to charging station is a meaningful index to balance the utilization ratios of charging stations in the charging station layout planning.

7. Conclusions

This study attempts to investigate the travel behavior of BEV drivers on charging and route choice. Different from traditional travel choice behavior modeling of GV drivers, a NL and PSL combined model with vehicle variables and charging station attributes is developed to reflect the charging decision-making and route choice process. With the quantified analysis, the proposed final model (M4) in this paper is more appropriate than traditional logit model on explaining BEV charging and route choice behavior.

Due to the significant influence imposed by BEV information and driver's characteristics, judgment of charging demand is explicitly analyzed using the proposed model. According to the findings, the initial SOC is the most important factor that higher possibility of charging caused by lower initial SOC. Furthermore, when the drivers are female or have high education level, the positive tendency has been observed for choosing charging since they are more discreet than the others. In contrast, the drivers who have high income or worked for highly profitable profession are inclined to no-charging.

To capture the difference of route choice behavior between BEV drivers and GV drivers, the route choice behavior is also analyzed using the proposed models. The goodness of fit of the models is reasonable and the data used in these models is found to be appropriate. Therefore, findings can be meaningfully interpreted for the charging and route choice behavior. According to the estimation results, the energy consumption influenced by route and vehicle's attributes has impacts on the BEV drivers' route choice behavior with no-charging. However, the route choice behavior with charging is significantly influenced by the information of charging station and vehicle's attributes. The results show that the drivers are inclined to choose the routes with charging station which is closer to origin and consistent with the direction from origin to destination.

Furthermore, to capture the effects of range anxiety on charging and route choice behavior, three transformations of SOC variables have been presented. The results show that pessimistic attitude for cruising range is more suitable to describe the charging and route choice behavior of BEV drivers. A numerical example verified that the existence of a basic value for comfortable initial SOC and the slope of comfortable initial SOC values increases gradually with travel distance increasing, caused by the pessimistic attitude for cruising range. Finally, the sensitive analysis of charging time and distance from origin to charging station to charging route choice shows that the deviation of the probabilities is proportional to the deviation of charging time or distance from origin to charging station.

The conclusions of this paper are helpful to analyze spatial and temporal characteristic of BEV flexible charging demand and solve charging station location problem. With the widespread adoption of EVs and construction of charging infrastructures, the traffic flow is viewed to be significantly influenced by the added presence of EVs. The utility function of the proposed model in this paper can be used to estimate the generalized cost function of BEV as the basis of traffic assignment. And combined the model proposed in this paper and the GV drivers' travel behavior model in previous researches, the traffic assignment analysis for mixed flow with EVs and GVs will be a further expansion. In addition, although the charging cost rates are assumed to be unique for different charging stations in this paper, considering the charging cost in charging station has been involved in the travel cost, so the impacts of different charging cost rates can also be captured by varying travel cost in further studies.

Furthermore, considering the preference heterogeneity across individuals, a latent class will be combined with the nested logit model to examine differences between segments of BEV drivers and a comprehensive analysis for BEV drivers' charging and route choice behavior will be discussed. Meanwhile, considering the demand for comprehensive and accurate information of BEV drivers to ensure completing their trips without running out of charge, it is an important point to analyze the potential different impacts on the charging and route choice behavior of BEV drivers between fuzzy pre-trip information provision and quantitative pre-trip information provision. Several of these studies are in progress and will be subjects of future publications.

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