Journal of System Simulation

Volume 31 | Issue 3 Article 24

11-20-2019

Potential Users of Battery Electric Vehicle Based on Big Data of Floating Vehicles

Kong Yuan
1. Smart-city research center of Hangzhou Dianzi University, Hangzhou 310018, China;;2. Department of Civil Engineering, Tsinghua University, Beijing 100084, China;

Yiman Du
2. Department of Civil Engineering, Tsinghua University, Beijing 100084, China;

Jianping Wu
1. Smart-city research center of Hangzhou Dianzi University, Hangzhou 310018, China;;2. Department of Civil Engineering, Tsinghua University, Beijing 100084, China;

Kezhen Hu
2. Department of Civil Engineering, Tsinghua University, Beijing 100084, China;

Potential Users of Battery Electric Vehicle Based on Big Data of Floating Vehicles

Abstract

Abstract: Nowadays, the Chinese government is strongly pushing the adoption of new energy vehicles, so it is of great significance to find the most suitable users of EV (Electric Vehicle). *This paper did a data mining work to find out target user group of EV based on two-month traveling data, driver information and vehicle attribute information of 12,000 floating vehicles in Beijing.* The results show that residential area is more suitable to push the adoption of EV than other functional areas; adding charging piles in the destination area can turn the 9.2% of drivers who are not suitable for EV due to the maximum mileage into the potential users.

Keywords

electric vehicle, big data of floating vehicles, potential user, travel behavior, travel distance

第 31 卷第 3 期　　系统仿真学报©　　Vol. 31 No. 3
2019 年 3 月　　Journal of System Simulation　　Mar., 2019

Potential Users of Battery Electric Vehicle Based on Big Data of Floating Vehicles

Kong Yuan[1,2], *Du Yiman*[2], *Wu Jianping*[1,2], *Hu Kezhen*[2]

(1. Smart-city research center of Hangzhou Dianzi University, Hangzhou 310018, China;
2. Department of Civil Engineering, Tsinghua University, Beijing 100084, China)

Abstract: Nowadays, the Chinese government is strongly pushing the adoption of new energy vehicles, so it is of great significance to find the most suitable users of EV (Electric Vehicle). *This paper did a data mining work to find out target user group of EV based on two-month traveling data, driver information and vehicle attribute information of 12,000 floating vehicles in Beijing.* The results show that residential area is more suitable to push the adoption of EV than other functional areas; adding charging piles in the destination area can turn the 9.2% of drivers who are not suitable for EV due to the maximum mileage into the potential users.

Keywords: electric vehicle; big data of floating vehicles; potential user; travel behavior; travel distance

基于浮动车大数据的电动汽车潜在用户分析

孔源 [1,2]，杜怡曼 [2]，吴建平 [1,2]，胡可臻 [2]

(1. 杭州电子科技大学智慧城市研究中心，杭州 310018；2. 清华大学土木工程系，北京 100084)

摘要：在当前中国大力推动发展新能源汽车的政策背景下，发现最适合使用电动汽车的目标用户具有十分重要的意义。*该研究基于北京地区 12 000 辆浮动车历时两个月的海量行驶数据，结合相应的驾驶员信息、汽车属性信息等，交叉探索居民的出行特性，分析适合使用电动汽车的用户群体。*数据分析结果表明主要功能为居住的城市区域相对其他类型的功能区更适合推广电动汽车；如果在目的地区域设置充电桩，可使约 9.2%的本来不适合使用电动汽车的用户成为电动汽车的潜在用户。

关键词：电动汽车；浮动车大数据；潜在用户；出行行为；出行距离

中图分类号：TP391.9　　文献标识码：A　　文章编号：1004-731X (2019) 03-0575-10

DOI: 10.16182/j.issn1004731x.joss.17WJP-013E

Introduction

New energy vehicles, especially battery electric vehicles, are taken as a promising green transportation and a vital mean to solve the current urban air pollution and energy issues. At present, China's new energy vehicle industry is still in the initial stage of development. Market cultivation and expansion are key factors hindering its advancement. The Chinese government has actively formulated corresponding policies to vigorously support the development of this industry. Meanwhile, the central and local governments give a large amount of subsidies for the purchase of new energy vehicles[1]. Automobile manufacturers and related academic departments highly advocate the promotion of new energy vehicles as well. However, due to the fact that

Received: 2016-12-13　　**Revised:** 2017-01-06;
Authors: Yuan Kong(1985-), male, Henan, Ph.D. candidate, Research direction: ITS, Big Data; Du Yiman(1977-), female, Sichuan, Ph.D., Research direction:traffic simulation; Wu Jianping(1957-), male, Zhejiang, PH.D., professor, Research direction:traffic modeling.

most of the domestic researches are limited to the qualitative discussions on promotion barriers in China market and preferential policies[2-4]. Very few researchers are able to consider and study ways to promote the development of new energy vehicles from the perspective of customers. Therefore, in order to solve the problem that such vehicles are highly advocated but with an extremely low purchase rate, it is essential and of great practical significance to conduct quantitative researches on the groups of users. Finding potential users can provide specific targets for the promotion and explore the potential users' demands so as to turn them into actual users. With China's capital, Beijing, as the object of study, considering the characteristics of battery electric vehicles and massive information of floating vehicles, this paper aims to find out the potential users that are most suitable for the use of electric vehicles, and provide more effective information for the promotion, thus facilitating the rapid advancement of new energy vehicle industry.

The traditional questionnaire survey is rather time-consuming and laborious. In addition, due to the uncertainty caused by subjectivity, there may be omissions and misstatements. For instance, the user may not be able to provide accurate information of their daily travel time, frequency and distance[5]. Moreover, limited by factors such as human resources and financial resources, questionnaires are often confined to partial group of users. Therefore, the sample size always tends to be small so that the overall characteristics can't be fully reflected. With the progress of science and technology, electronic devices are more and more used in the traffic data collection, and massive traffic data of various types have been accumulated. Traffic big data has brought unprecedented changes to the intelligent transportation industry[6]. In particular, various types of OBD or vehicle-mounted GPS equipment provide massive travel trajectory information. How to rapidly and effectively explore massive travel trajectory information of motor vehicle so as to uncover useful and deep semantic knowledge is an important aspect in the current researches of traffic big data. Based on the two-month traveling data, driver information and vehicle attribute information of 12 000 floating vehicles in Beijing, this paper explores residents' travel characteristics and analyzes the user groups that are more suitable for the use of electric vehicles based on travel distance, an important influence factor, which provides effective information for the promotion of electric vehicles.

1 Data collection and processing

1.1 Data description

The data used in this paper is based on the floating vehicle data of partial social vehicles in Beijing. It contains driving information (GPS data), driver attribute information and vehicle attribute information of 13 828 vehicles of various brands for two consecutive months (2012-07-01-2012-07-31).

The GPS information table in the database contains information such as vehicle ID, start time, geographical dimension, geographical longitude, instantaneous speed, instantaneous fuel consumption, travel distance, road grade, travel direction and GPS signal status. GPS information is recorded once per second and the total number of records reaches about 2 billion, taking up about 500 GB disk space. The driver information table contains name, phone number, gender, date of birth, driver's license type and other information (in order to protect user's privacy, name and phone number are encrypted); Vehicle information table contains information such

https://dc-china-simulation.researchcommons.org/journal/vol31/iss3/24
DOI: 10.16182/j.issn1004731x.joss.17WJP-013E

as vehicle brand, vehicle type, transmission type, purchase date, the weight, length and width of vehicle, the type of fuel used, vehicle use; the data of Beijing recorded by “Cn-map” navigation electronic map is used with the format of .map which is supported by Mapinfo software. Driver’s information can be learned by matching GPS trajectory with map and then matching associated fields with attribute database: for instance, the vehicle ID is 4 ***** 7, the driver is female aged 40 with C1 driver's license; and the information regarding vehicle of this trajectory: for example, the vehicle brand is Volkswagen equipped with manual transmission. It weighs 1 550 kg with 16 cc emissions. In addition, the fuel type is 93 #.

1.2 Data processing

The preliminary data analysis suggests incomplete or obviously abnormal data of some vehicles. For example, there is only GPS information while driver and vehicle information are absent; a large number of GPS data of some vehicles are missing. In the data preprocessing stage, these kinds of data are removed and ultimately data of about 12 000 floating vehicles are selected. Preliminary statistics of these 12 000 vehicles shows that there are about 4 000 vehicles with actual data on a daily basis for the two months. In particular, there are about 4 200 on weekdays and 3 800 on the weekends. The data quality is good with no obvious distribution abnormality.

The raw data is stored in Oracle database. The data collected by On-Board Diagnostic (OBD) is uploaded as package and ultimately stored in database as Binary Large Object (BLOB), which can’t be read directly. Therefore, it’s required to be parsed into the original records that are recorded once per second. Considering the large amount of data, travel trajectories are respectively stored in 10 database tables based on the last number of vehicle ID from 0 to 9 so as to improve the efficiency of database retrieval.

Faced with massive trajectory data, Python is applied to the multi-threaded batch data processing and extract travel information from database with the objective of rapidly analyzing travel mileage and characteristics. Considering that the travel of every vehicle in one day contains many trips with different purposes. Therefore, trip is taken as the basic unit for calculation and analysis[7].

The raw data is not divided based on each trip. Hence, screening is required during data processing. According to the time continuity of data and stay points of trajectory, the screening methods are as follows:

(1) If the GPS data of a vehicle is continuous for every second, this series of data will be considered to belong to one trip, as the GPS records once every second;

(2) The discontinuity in the recording time of GPS data may be caused by temporary stop or engine stalling so that it should still be considered as one trip. Therefore, if the end time of a series of GPS records is less than 3 minutes from the start of the next series of GPS records, the two trips are combined and taken as one trip.

The above trajectory partitioning algorithm is executed by SQL statement and its formula is expressed as follows:

$$\text{trip}=\begin{cases}1, & t_{i+1}-t_i<180\\ 0, & t_{i+1}-t_i\geqslant 180\end{cases}$$

The trip in the formula represents each trip. Trip=1 indicates that there’s only one trip and trip number remains unchanged. While if the result is 0, it

Published by Journal of System Simulation, 2019

suggests two different trips and trip number is increased by one. The unit of time t is second (s).

Due to the different road conditions, driver characteristics as well as vehicle and weather conditions, this algorithm can’t be applied to every vehicle. And yet one of the advantages of big data is the large data volume. Its accuracy requirement of data is not as rigorous as the small sample data. Hence, the interference caused by above situations can be ignored[8]. Judging from the actual results of the partitioning, preliminary observation and statistics found no obvious abnormal trajectory partitioning.

2 Data analysis methods

There are many factors influencing the purchase of electric vehicles. From users’ points of view, the main factors include gender, age, occupation, family income, number of vehicles owned as well as environment protection awareness[9]; from the perspective of vehicle performance, the main factors are maximum mileage, charging time, charging convenience, cell lifespan as well as vehicle price and performance. According to the survey, 93.65% of users believe that the maximum mileage that electric vehicles can reach after being fully charged is a vital factor affecting their willingness to drive electric vehicles[10]. This study is based on the driving data analysis of floating vehicles, instead of the traditional way of carrying out questionnaire survey on users. In the data-driven context, this paper mainly considers travel distance, an important influencing factor, and combines the information of users and vehicles to conduct comparative analysis on potential user groups.

Most existing GPS-based trip analysis are based on taxi GPS data and do not contain information about driver or vehicle attributes[11-13]. Yet some studies conducted on the basis of ordinary vehicles contains merely a small sample of experimental GPS data[14-15]. The travel distance characteristics of different types of groups are analyzed comprehensively based on the high-precision (1HZ sampling rate) mass GPS information of social vehicles in two months as well as the corresponding attribute information of drivers and vehicles. This paper primarily analyzes the travel distance characteristics of users in different urban functional areas, and makes a comparative analysis of the travel distance distribution based on driver gender and vehicle use (private vehicle or official vehicle). Meanwhile, travel distance on weekdays and weekends are compared and analyzed.

As China's electric vehicle market is still in the initial stage of development, it currently accounts for a small share in the overall vehicle market, and there is no effective way to obtain its driving data for the time being. The data used in this study are derived from conventional fuel vehicles, so it is necessary to make the following assumption before analyzing the mileage suitability of electric vehicles: people will transfer their daily travel habits of traditional fuel vehicle to the daily use of electric vehicles, that is, their travel characteristics basically remain the same[16].

3 Travel distance analysis

3.1 Analysis on average daily travel distance of vehicles

According to the field information of travel distance, the total daily travel distance of all vehicles during the two-month period are statistically analyzed to obtain the average daily travel distance distribution. The results are shown in Fig. 1, wherein the horizontal axis represents travel distance and the vertical axis represents daily average vehicle number.

https://dc-china-simulation.researchcommons.org/journal/vol31/iss3/24
DOI: 10.16182/j.issn1004731x.joss.17WJP-013E

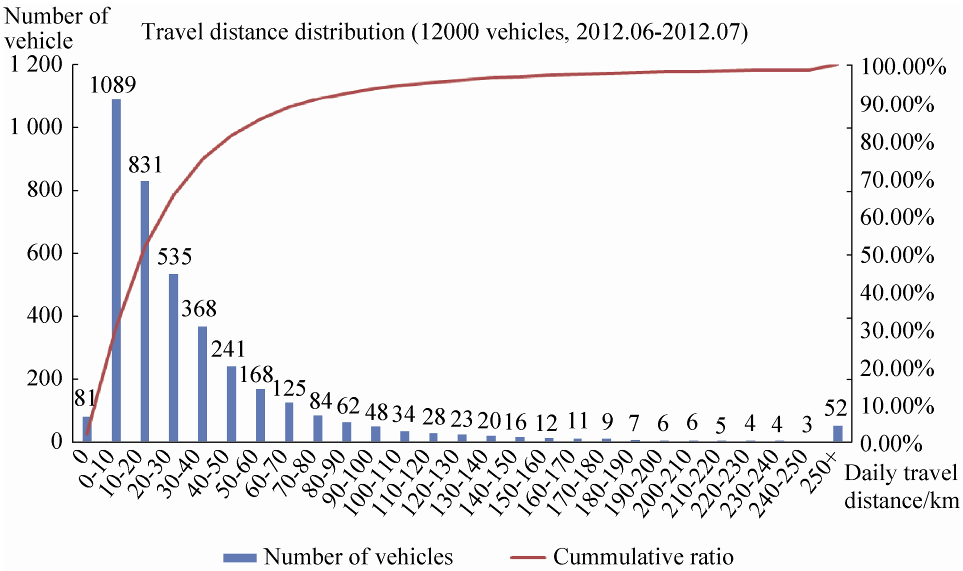

Fig. 1 Overall travel distance distribution

The analytical results show that the overall travel distance of residents is subject to long-tailed distribution. The daily travel distance of 80% residents are within 50 km, while the residents that travel over 100 km averagely on a daily basis accounted for less than 6%. 50% of the residents travel less than 20 km averagely on a daily basis. In the current market, the maximum mileage of mainstream electric vehicles is within 120–200 km, which is able to satisfy the daily travel needs of vast majority of residents. Since half of drivers travel within 20 km, a weekly full charging of cell is able to meet the travel needs for a whole week. The travel distance calculation model can retrieve and locate this part of users who are more suitable for travelling in electric vehicles from the database. There’s no need for them to often charge the electric vehicles so that they will not be affected by the excessive restrictions of charging convenience problems. For instance, the public charging pile is currently insufficient in city and it can’t be installed at home.

3.2 Analysis on travel distance characteristics of different areas

As the main functions of various urban areas of Beijing are different, five types of functional areas[17] are selected with a square area of 4 square kilometers each, including the commercial functional area represented by Wangfujing and Sanlitun, the educational functional area represented by the surrounding area of Shuangqing Road, the tourism functional area represented by the surrounding region of Tian’anmen, the residential functional area represented by surrounding area of Wangjing as well as background area that does not have a specific function. The area selection is shown in Fig. 2.

The first step is to analyze the average daily travel distance of vehicles departing from these five functional areas. A vehicle can be considered to belong to this area under the circumstance that the first record of this vehicle in a day is departing from this area. The average daily travel distance of vehicles in their departure area is shown in Tab. 1.

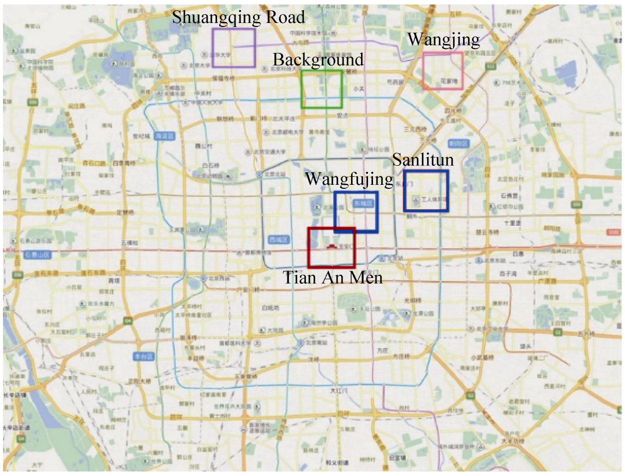

Fig. 2　Functional area selection

Tab. 1　Average daily travel distance of vehicles in their departure area　/%

Average daily travel distance/km	Background area	Wangfujing and Sanlitun	Shuangqing Road	Tian'anmen	Wangjing
0	0.29	0.73	0.75	0.84	2.36
0~10	19.28	20.23	17.74	18.46	46.37
10~20	29.09	28.97	30.19	27.27	17.48
20~30	19.12	19.97	24.15	22.38	10.19
30~40	10.93	10.08	8.30	10.77	6.35
40~50	7.31	6.47	6.04	6.01	3.97
50~60	4.63	4.15	3.02	4.90	3.17
60~70	2.76	2.31	2.64	2.24	2.33
70~80	2.08	1.57	0.75	1.82	1.45
80~90	0.84	1.79	1.89	0.55	1.28
90~100	0.83	1.32	1.13	1.26	0.94
100+	2.85	2.42	3.40	3.51	4.12

It's discovered that 48.73% of the vehicles departing from residential functional area (Wangjing) travel 0 to 10 km on a daily basis, which is far higher than the other four areas. In addition, there is no significant difference in the average daily travel distance among the remaining four areas. Users with shorter travel distance are believed to be less affected by the maximum mileage of electric vehicles, making users in residential functional area more suitable to drive electric vehicles than other types of functional areas. Hence, it's advised to focus on the publicity and promotion of electric vehicles in the residential areas.

Moreover, adding charging piles in the destination can enhance the charging convenience, thereby turning a portion of users who are not originally suitable to drive electric vehicles into potential users. Therefore, it's necessary to analyze the average daily distance of vehicles after they arrive at the functional areas. In the meantime, the cell of mainstream electric vehicle can be charged over 80% by using fast charging pile for 2 h. Therefore, this paper locates the vehicles that arrive at the functional areas at daytime 6:00-18:00 with more than 2 h parking time, and conducts statistical analysis on their travel distance. The results are shown in Tab. 2。

Tab. 2 Average daily travel distance of arrived vehicles /%

Average daily travel distance/km	Background area	Wangfujing and Sanlitun	Shuangqing Road	Tian'anmen	Wangjing	Average
0	0.50	0.57	0.69	0.56	2.39	0.94
0~10	38.84	27.90	20.27	24.29	32.44	28.75
10~20	24.94	27.87	34.71	26.34	19.88	26.75
20~30	13.03	17.50	22.51	21.25	13.41	17.54
30~40	7.11	7.85	6.53	8.36	9.06	7.78
40~50	4.68	5.67	4.81	6.86	6.05	5.61
50~60	2.37	3.50	3.09	3.76	4.46	3.44
60+	8.54	9.15	7.39	8.59	12.31	9.2

The results show that 12.31% of the vehicles with residential functional area (Wangjing) as destination and more than two hours of parking after arrival have an average daily travel distance of 60 km or more, which is slightly higher than the other four areas. In addition, there's no significant difference among those four areas. Given the above analysis, residential functional areas are more suitable for additional charging piles compared to the other four functional areas. The users with an average daily travel distance of 60 km or more are subject to the maximum mileage limit, making them unfit for the use of electric vehicles. However, increasing charging pile at destination is able to solve the charge problems to satisfy their travel demands. Therefore, in general, 9.2% of the users with the daily trip distance of over 60 km can become potential users of electric vehicles by adding charge piles at destinations.

3.3 Comparative analysis on trip distance of different gender

The daily travel distance of male and female are compared statistically based on the gender field in drivers' information table, and the results are shown in Tab. 3。

The results suggest that 50.25% of the male drivers travel within 30 kilometers per day and 54.71% of female drivers travel within 30 kilometers every day, which is 4.46% higher than male drivers. In general, male drivers prefer longer-distance travel than female. Hence, from the point of view of electric vehicle mileage, female drivers are more suitable for the use of electric vehicles than male drivers. A weekly full charging of cell is able to meet nearly 55% of female drivers' travel demands for a whole week. In this case, driving electric vehicles will not severely affect their daily travel.

Tab. 3 Comparison of average daily travel distance between male and female

Average daily travel distance/km	Male/ %	Female/ %	Difference/ %
0	2.12	2.01	0.11
0-10	27.31	30.16	–2.85
10-20	20.82	22.54	–1.72
20-30	13.71	13.76	–0.05
30-40	9.54	9.31	0.23
40-50	6.42	5.93	0.49
50-60	4.51	4.02	0.49
60-70	3.44	3.07	0.37
70-80	2.29	2.12	0.17
80-90	1.77	1.06	0.71
90-100	1.35	0.95	0.40
100+	6.37	5.08	1.29

3.4 Comparative analysis on travel distance of different vehicle uses

On the basis of vehicle use information in the vehicle attribute information table, the daily travel

第 31 卷第 3 期 系统仿真学报 Vol. 31 No. 3
2019 年 3 月 Journal of System Simulation Mar., 2019

distances of private vehicles and official vehicles are compared statistically. The results are shown in Tab. 4。

Tab. 4 Comparison of daily travel distance between private vehicles and official vehicles

Average daily travel distance /km	Private vehicles/%	Official vehicles/%	Difference/ %
0	2.05	2.29	–0.23
0~10	28.44	24.84	3.60
10~20	21.60	20.26	1.34
20~30	13.87	13.40	0.47
30~40	9.51	9.48	0.03
40~50	6.19	6.54	–0.35
50~60	4.30	4.90	–0.60
60~70	3.15	3.92	–0.77
70~80	2.14	2.61	–0.48
80~90	1.55	2.29	–0.74
90~100	1.21	1.63	–0.42
100+	5.99	7.84	–1.85

The results demonstrate that 63.91% of the private vehicles travel 0~30 km per day, and 58.5% of the official vehicles daily travel 0~30 km. In terms of short-distance travel, the private vehicles are 5.41% higher than official vehicles. While in long-distance travel, official vehicles are 1.85% higher than private vehicles, indicating an insignificant difference. It's speculated from actual situation that some private vehicles are used for money-making purpose, thus increasing the proportion of private vehicles in the long-distance travels. Generally speaking, official vehicles are more used for long-distance travel compared to private vehicles. In light of the maximum mileage of electric vehicles, official vehicles are unfit for the use of electric vehicles.

3.5 Comparative analysis on travel distance between weekdays and weekends

In accordance with the time field information in the vehicle travel trajectory, the daily travel distance during weekdays and weekends are statistically analyzed. The results of the comparative analysis are shown in Tab. 5:

Tab. 5 Comparison of travel distance between weekdays and weekends

Average daily travel distance/km	Weekdays/ %	Weekends/ %	Difference /%
0	1.99	2.40	–0.41
0~10	28.70	26.50	2.20
10~20	22.37	18.87	3.50
20~30	14.14	12.87	1.28
30~40	9.55	9.40	0.14
40~50	6.07	6.65	–0.58
50~60	4.21	4.71	–0.50
60~70	3.08	3.68	–0.60
70~80	1.99	2.70	–0.71
80~90	1.48	2.00	–0.51
90~100	1.12	1.53	–0.41
100+	5.29	8.69	–3.40

It's discovered that the proportion of users with an average daily travel distance of more than 60 km on the weekend is 18.6% while the proportion on weekdays becomes 12.96% which is 5.64% lower than the weekdays. As far as the super long-distance travel over 100 km is concerned, the proportion on weekends is 3.4% higher than the weekdays. It proves that some of the users prefer long-distance travel on weekends. Provided that the use of electric vehicles affects these users' weekend travel needs, similarly, travel distance calculation model should be able to retrieve and locate them from database so as to provide them with more appropriate recommendations. As for those who don't travel long distance on the weekends and have regular and short-distance travel on the weekdays, it's advised to focus on guiding them to use electric vehicles, as they are rather suitable.

https://dc-china-simulation.researchcommons.org/journal/vol31/iss3/24
DOI: 10.16182/j.issn1004731x.joss.17WJP-013E

4 Conclusions

Cross-exploration is carried out according to the statistical analysis of the two-month travel distance information in nearly 2 billion travel records regarding 12,000 vehicles as well as the departure and arrival of vehicles in different urban functional areas, driver 's gender and vehicle use. The results suggest that residents' daily travel distance distribution conforms to the long-tailed distribution. The average daily travel distance of 80% residents is within 50 km. Currently, the mainstream electric vehicles on the market are able to meet the daily needs of the vast majority of residents, especially when half of the drivers averagely travel within 20 km on a daily basis. In this case, a weekly full charging of cell is sufficient to satisfy their daily travel needs. Travel distance calculation model can be applied to retrieve and locate these users who are more suitable to travel in electric vehicles from database. As there's no need for them to often charge the cell, they will not be severely affected by charging convenience issues. For instance, there's currently insufficient charging piles in the city and the piles can't be installed at home. Adding charging piles in the destination areas enables the 9.2% of the users who would otherwise be unsuitable for the use of electric vehicles to become potential users. Female driver prefer short-distance travel, which makes them more suitable to drive electric vehicles. A full charging of cell is required on a weekly basis to meet their travel needs for a whole week. Official vehicles are often used for long-distance travel, which is why electric vehicles are inapplicable for official purpose. 8.69% of users prefer long-distance travel on the weekends. Thus, driving electric vehicles will affect their weekend travel needs.

This study facilitates the researches on promoting the development of new energy automobile industry to a certain extent from the perspective of consumers of new energy vehicles. In addition, the above findings allow consumers to be more aware of their actual demands for vehicles. It's recommended that government and new energy vehicle manufacturers should enhance the knowledge publicity of electric vehicle endurance mileage in the promotion so that consumers can learn more about new energy vehicles and have more faith in it, ultimately facilitating their positive attitude towards purchase.

References:

[1] Development Plan of Energy Saving and New Energy Automobile Industry (2012-2020)[R]. China: State Council of the People's Republic of China, 2012.

[2] Wu Yong, Approach on Problems of New Energy Automobile Development[J]. Automobile Maintenance(S1009-2625), 2009, 21(7): 1-3.

[3] Fang Minzhou, Huyan. An Analysis of the Tax Preferential Policy Effect for the Rapid Promotion of the New Energy Automobile[J]. Auto Mobile Science& Technology(S1005-2550), 2009, 29(5): 7-10.

[4] Xu Xiao, Wang Qiaofeng, Zhou Rong. Problems and Solutions of New Energy Automobile Development[J]. Shanghai Auto, 2009, 19(5): 8-10. (In Chinese)

[5] Zhang Junfeng. Research on Travel OD Based on GPS Technology[D]. Beijing: Beijing Jiaotong University, 2011.

[6] Lu Huapu, Sun Zhiyuan, Qu Wencong. Big Data and its Application in Urban Intelligent Transportation System [J]. Journal of Transportation Systems Engineering and Information Technology(S1009-6744), 2015,15(5):46.

[7] Yin Huaxing. Route Mining and Retrieval Based on Mass Spatio-Temporal Data[D]. Hefei: University of Science and Technology of China, 2012.

[8] V Mayer-Schonberger, Neil Cukier. BIG DATA[M]. London: Hodder Export, 2013.

[9] A Namdeo, A Tiwary, R Dziurla. Spatial planning of public charging points using multi-dimensional analysis of early adopters of electric vehicles for a city region [J]. Technological Forecasting & Social Change (S0040-1625),

2014, 89(6): 188-200.

[10] Zhao Bin. Study on the Influencing Factors of Purchase of BYD New Energy Vehicle[D]. Changsha: Central South University, 2010.

[11] Lu F, Duan Y Y, Zheng N B. A practical route guidance approach based on historical and real- time traffic effects[C]. Proceedings of the 17th International Conference on GeoInformatics, Fairfax, USA, 2009:12-14.

[12] Tong Xiaojun, Xiang Nanping, Zhu Dingju. Analysis on Urban Residents' Travel Behavior Based on Taxi GPS Data[J]. Applied Technology and Research(S1008-6609), 2012, 23(1):56-59.

[13] Wei Xiang. Research on Detection Method of Taxi Behavior Based on Big Data Mining[D]. Chengdu: Southwest Petroleum University, 2015.

[14] Etter V, Kafsi M, Kazemi E, et al. Where to go from here? Mobility prediction from instantaneous information [J]. Pervasive and Mobile Computing, 2013, 9(6): 784-797.

[15] Do T M T, Gatica-Perez D. Where and what: Using smartphones to predict next locations and applications in daily life[J]. Pervasive and Mobile Computing (S1574-1192), 2014, 12(6): 79-91.

[16] Zhang Zhihua. Research on Travel Information Extraction Based on GPS Trajectory[D]. Shanghai: East China Normal University, 2010.

[17] Hu D M, Zhou Y, Xu M, et al. Identifying regional service function from $PM_{2.5}$ mass concentration throughout a city with non-negative tensor factorization approach[J]. Environmental Science and Pollution Research (S0944-1344), 2015, 14(8): 1-4.