“UNEARTHING THE ENVIRONMENTAL IMPACT OF HUMAN ACTIVITY: A GLOBAL CO2 EMISSION ANALYSIS”

Submitted in partial fulfillment of the requirement for the Degree of **BACHELOR OF SCIENCE IN PHYSICS**

SUBMITTED

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BONAFIDE CERTIFICATE

This is to certify that **Ms\Mr. NIRMALRAJ.S (REG.NO:222003997)** had done a project report titled **“VISUALIZATION TOOL FOR ELECTRIC VACHILE CHARGE AND RANGRE”** in partial fulfillment as per requirement for the degree on **BACHELOR OF SCIENCE IN PHYSICS** from APOLLO ARTS AND SCIENCE COLLEGE, POONAMALLEE, CHENNAI.

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DECLARATION

I hereby declare that the project work entitled is " **VISULALIZATION TOOL FOR ELECTRIC VACHILE CHARGE AND RANGE** " an original work done by me in a fulfillment for the degree of **BACHELOR OF SCIENCE IN PHYSICS from APOLLO ARTS AND SCIENCE COLLEGE, POONAMALLEE, CHENNAI**, Which is carried off under the guidance of**, Mrs.MAHENDRAN HEAD OF THE DEPARTMENT** during JANUARY 2023 TO MAY 2023.

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The project is completed with the support of many persons .With pleasure I express my sincere thanks to all of them. I wish to take this opportunity to thanks.

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ABSTRACT

Recently, more and more countries decided to develop electric vehicles especially electric car. However, because of low prices and other issues, electric bicycles have become the most popular electric transportation vehicles in many developing countries. For example, there are more than 210 million electric bicycles in China. Large-scale electric bicycle charging demand from time to space will not only has an impact on power distribution grid, but also has demand side management (DSM) value. In this paper, we introduced a method for estimating the realtime charging load for electric bicycles. Then we visualized demand in space using heat map and power density node. The numerical results illustrate that large-scale electric bicycle charging demand not only has a great peak-valley but also exhibits unbalance in space.

INTRODUCTION

Electric bicycles have many advantages such as low cost, energy saving, and simple to use. By the end of 2015, China has 210 million electric bicycles [1]. Single electric bicycle charging load is only around 100~200W. However, when the total number of electric bicycles reach millions, its overall load cannot be ignored.

With great randomness and uncertainty, millions of electric bicycles charging load will cause a certain degree of impact on power distribution network. The disordered charging behavior of electric bicycles may be superimposed with domestic electricity demand, leading to the problem of "peak-plus-peak", which affects the safety and reliability of power transformers, especially those with smaller capacity. Moreover, due to the combustion characteristics of lead-acid batteries, large-scalĺe electric bicycle charging will cause fire hazards. These two issues are urgent need to know by local electricity company.

With the explosive growth in the number of electric vehicles, investigating the impact of large scale electric vehicles charging behavior has received much attention. Numerous studies have given insights into large scale electric car charging influence, Diana et al conducted a systematic literature reviews and conclude there are mainly two approaches, environmental analyses as well as in travel demand analysis [2].

Using conventional cars data to simulate electric vehicles (EVs) use patterns, Michele et al use GPS tracer to collect gasoline vehicle travel information, and simulate the influence of electric vehicle charging behavior on power grid [3]. Moreover, this study also uses heat map to visualize the charging demand on map. Darabi and Ferdowsi use US National travel survey to estimate demand curve [4]. However, some researchers point out the scenarios for using EV is different from conventional cars [5].

For direct measure, data from electric vehicle charging pile are used in [6], and a Monte Carlo model is applied to analyze the influence to power network. Since electric bicycle as a special transportation in China.

Rare of studies proposed similar study. Moreover, different from EVs which could find a reference objective (i.e. conventional car).

There is no suitable reference for electric bicycle travel information because travel distance for an electric bicycle is much more higher than a conventional bicycle.

This paper aims to study the influence of large scale electric bicycle charging in space and time. For this purpose, we conducted online survey which could collect geographic information about where users charge their bi We simulate real-time demand curve, and then estimated the influence of electric bicycles charging in space domain using a model based on heat map. T

he remainder of the paper is organized as follows. Section Ⅱ introduces methodology including dataset. Section Ⅲ presents results with discussion, In order to better understand the electric bicycle charging behavior, we will refer to the existing electric vehicle research for comparison in this section. We conclude with suggestions in Section Ⅳ.

II. METHODOLOGY

A. Data This study is based on the analysis of databases from Nanning, a city with a total population of around 7 million people in China (3m urban citizens, 1.7m electric bicycles). The data were collected through online questionnaire.
B.

The questionnaire was administered in local electricity social media platform. The survey consists of two parts. Firstly, a map was shown with a question to collect charging location including longitude and latitude.

Second, fifteen questions were designed through which we identify user's general information and daily energy consumption. Lastly, select the samples which meet the requirement. In this case study, the main selected factors are city

C. Background and sample characteristic Table Ⅰ provides the background information for our case study city. The entire area of Nanning, including the county has 7 million people, and 3 million live in the urban.

Electric bicycle are the main transportation tool for urban citizen with a total of 1.7 million. Majority of electricity bicycle use Leadacid batteries, and Mainly divided into three battery models 48V,60V, 72V [7]. In general, travel mileage is proportion to voltage rate.

TABLE I. BACKGROUND OF CASE STUDY CITY

Name of city	Population of Citizens	The population density	Whether to prohibit motorcycles	Per capital GDP
Nanning	7 M(3M urban citizen) (2015/6/11)	334/ km 2	YES	7919 USD (2015)

The survey consists of two part, at part one respondents will see a map and a question to indicate the most frequently charged place, more than 2000 sample was recorded in Nanning. Next, an online questionnaire consist of fifteen questions was shown, each question is in a separated page. Only a questionnaire that answers all question will be considered as a valid questionnaire. This section could be divided into two parts, part one is general information (gender, age, education level etc.), we analysis the data based on part two(type of battery, voltage level of battery, brand, travel distance, charging frequency, charging duration etc.). the potential answer was designed into the option. For example, there are 24 options for question ‘when will you start to charge your bike’ and 5 options ranges from 0 to over 40 for question ‘how long will you travel each day’. Summary of data was show in Table II.

TABLE II. SUMMARY OF DATASET

Number of examples	Average travel distance(KM)	Average charging frequency (Days)	Charging duration(Hours)	Average age of bicycle(years)
1574	14.54	1.98	7.05	2.35

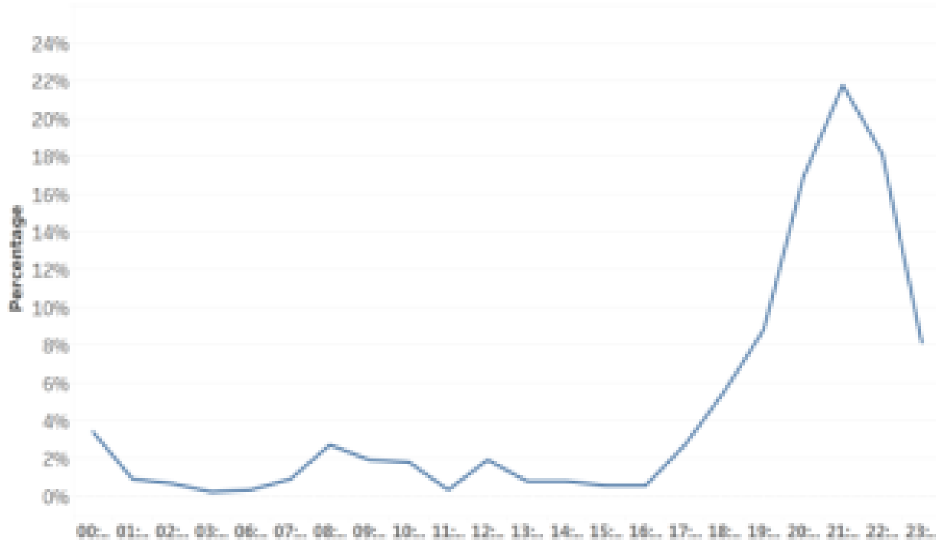

Fig. 1 shows the distribution of charging starting time of electric bicycle users. From the distribution we can see that most users began to charge in the evening, and it witnessed a rapid growth from 17:00 to 22:00.

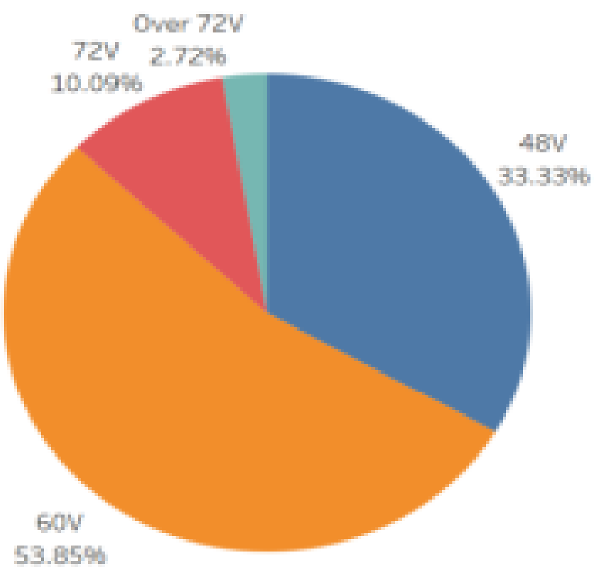

Fig. 2 illustrates the proportion of different Lead-acid voltage type. 60V are the most popular following with 48V while over 72V are the smallest.

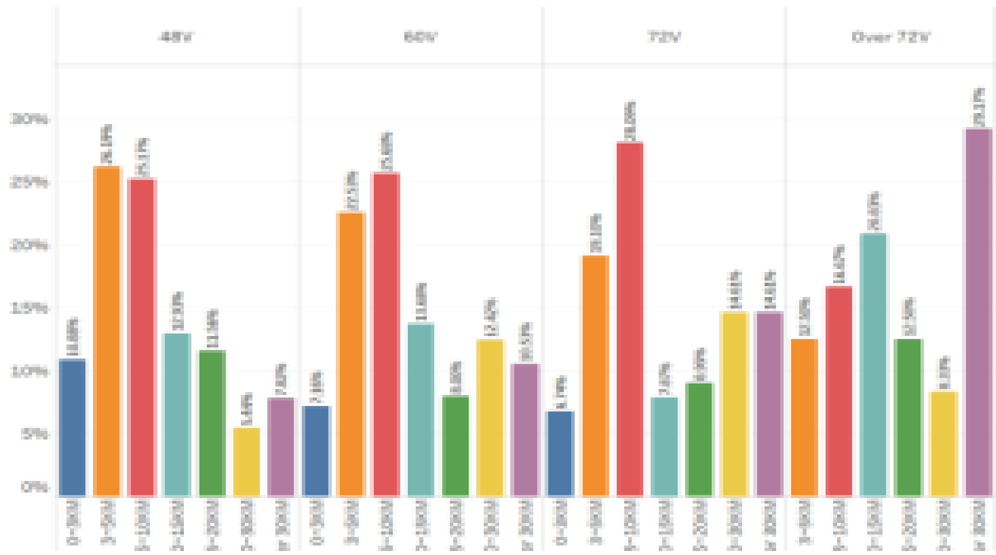

Fig. 3 Travel distance according VS different lead-acid voltage

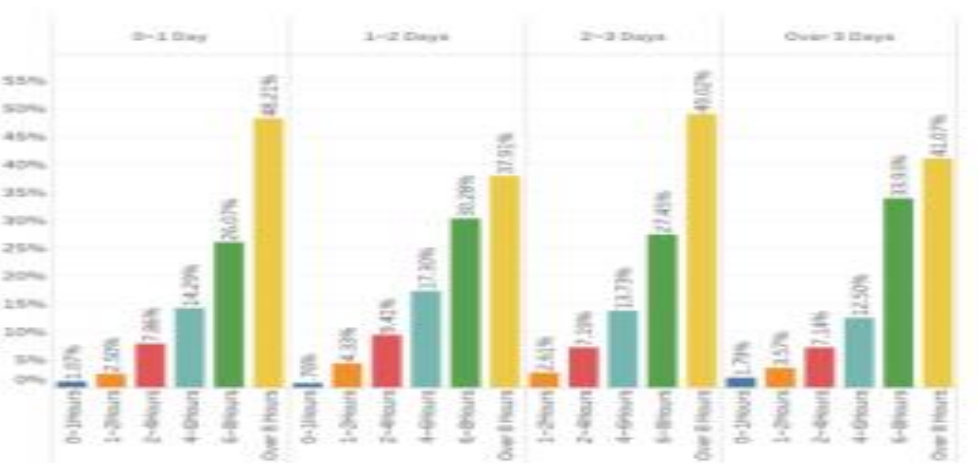

Fig. 4 Charging frequency VS charging duration

Fig 3 of travel distance VS lead-acid voltage type indicates that, when a electric bicycle had higher voltage, the travel distance will be longer.

Fig. 4 shows the travel distance according to different type of voltage. Fig. 5 demonstrate the charging frequency according to charging duration in one period. The results show that different group of users have different behaviors.

Real-time model We fit a real-time model to overlay different charging load for different samples in the dataset and obtain the total demand curve.

Because the power of battery charging is not constant, most researchers consider different charging models based on battery type [3]. In our case study, Lead-acid batteries [8] account for a majority. Therefore, following [9], we employed the typical three-stage charging model for Lead-acid batteries.

At the first stage, corresponding to the power, 70% of energy was charged. At the second stage, the rest 30% was charged and power decreased linearly. At the last stage power was cut to zero.

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Equation (1) models the first stage charging time for a bicycle, Equation (2) for the second stage, and Equation（3） calculates the total energy for the whole city.

This model can estimate the total charge load curve by imposing different charging curves of electric bicycle

$$T = P\ S \times K \quad (1) \qquad t = p\ (S \times K) - (P \times T) \quad (2) \qquad \text{Total Energy} = \quad (3)$$

Where: T is the charging time of the constant power stage; t is the charging time where power decrease linearly; S Electric bicycle power consumption at unit distance; K distance of travel; P constant stage charging power; p linear decrease charging power; n number of examples; N number of population.

Space model The space model is an embedded program based on BAIDU heat map applications [13]. Firstly, we collected the geographic latitude and longitude information.

Then we set the appropriate latitude and longitude tolerance level, which allows all the data points within tolerance range to merge into the same point. Finally, The results were demonstrated in heat map and power density node. A heat map is a graphical representation of data where the individual values are represented as colors. However, the characteristic of a heat map is to visualize summary information, and could not reflect the details of energy demand. Therefore, in order to analyze the demand of each area, we created a concept on map called power density node. Power density node is a node where the number of merged points will be shown.we calculated the power density.

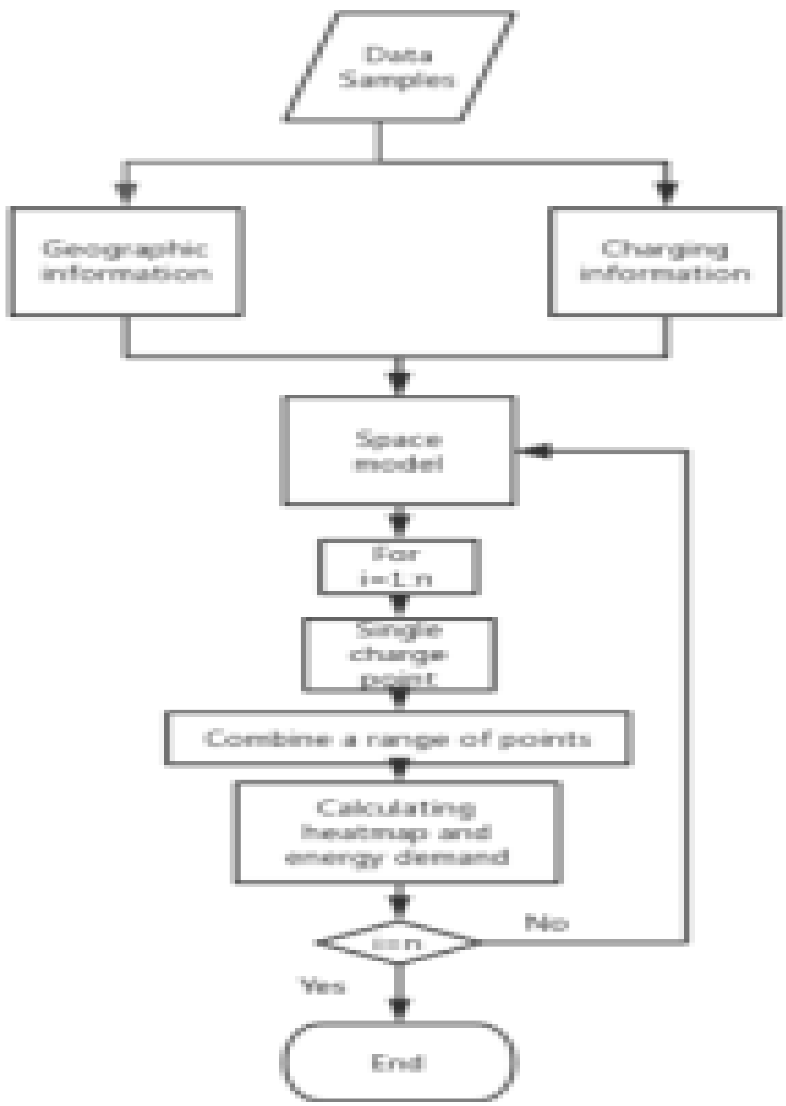

Fig. 5 Space model research flow chart

Equation (4) calculates the energy demand for each number. Equation (5) calculates the energy demand for each node on the map. For examples, if there is a number of 10 on node, it means there are 10 times of energy demand from (4).

This study explores the influence of 1.7 millions electricity bicycle charging impact from time to space aspects. In the following paragraphs the results of real-time and space model are presented.

In the space model, the most significant results were derived from the heat map to evaluate the influence of electric bicycle charging to distribution network.

A. Results of space model

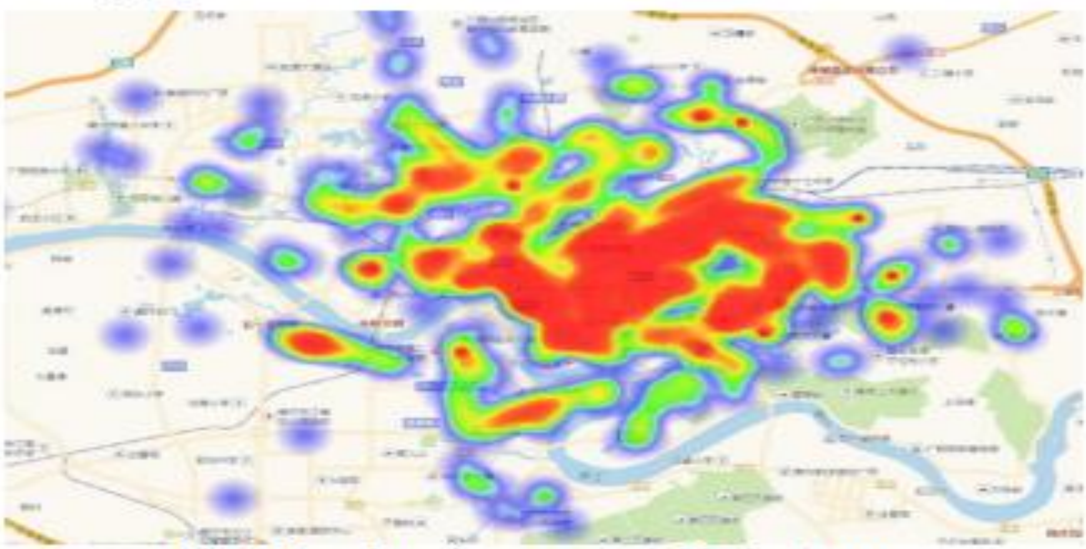

Fig.6 Results of space model in heat map

The heat map was divided into three colors to represent charging density. Red represents the most concentrated area of charge, followed by yellow, green last.

. 6 shows the results of heat map. Charging demand of electric bicycles presents a trend of concentration. The area in red are mainly city centers or shopping malls where people often work and live. This also witnessed in other electric car studies [3,12]. Surprisingly, the suburban load demand is very small, which is subject to the electric bicycle's travel ability and the density of residents.

By comparison with results from other EVs studies, charging demand distribution for EVs is wider than our results.

In order to precisely estimate the impact of demand side management value, we use specify number which is proportional to the number of questionnaires to reflect the demand on map.

Fig.7 shows the results of power density node. The mean daily demand is 12.54 MWh. From this figure, the imbalance of demand distribution is further explained. The highest demand (86 MWh) is 43 times to lowest (2 MWh).

This finding indicated that charging demand for electric bicycle on space have a high demand side management value; decentralized charging can reduce the risk of generate congestion at bottlenecks in the distribution network.

Moreover, guiding electric bicycles scattered charge could reduce the investment and operating fee for distribution grid capacity. This method could show the detail of energy demand, which is improved compare to Michele’s study[3].

Fig.7 Results of space model in power density node

B. Results of real-time mode

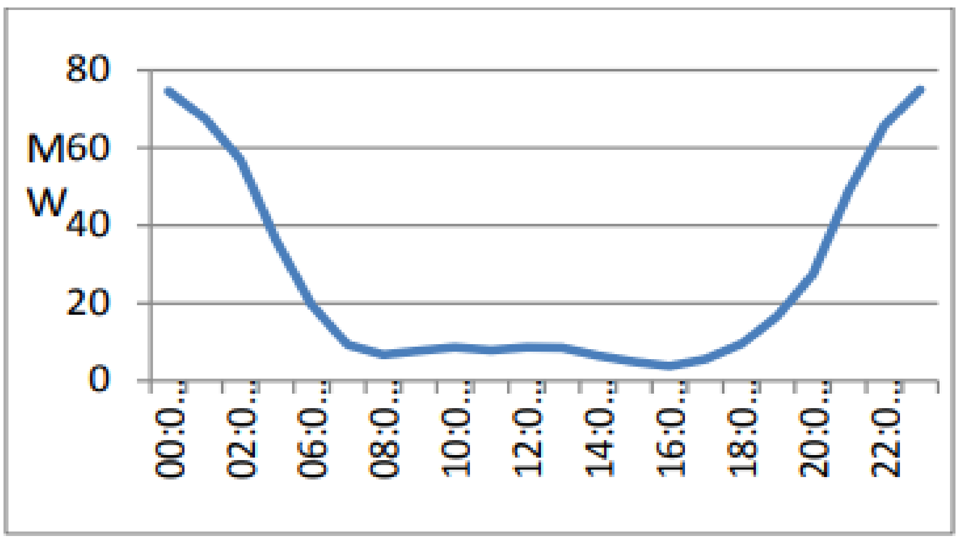

Fig.9 Results of real-time model

TABLE III. RESULTS OF REAL-TIME MODEL

Total Demand a day (MWh)	Max. Demand (Mw)	Min. Demand (Mw)	Max./Min. Ratio	Average Load power (Mw)
627.12	74.6	3.78	19.73	26.13

The curve from real-time model describe the demand on an hour resolution. As shown in Fig.9, the demand curve is low in middle and high on both sides especially at night hour. Must be noted that the get off work time in Nanning is 5 pm, which happens to be the demand curve began to rise time. For the reason of comparison, we defined 18:00 to tomorrow 7:00 as charging peak hours; over 80% of energy was charged during this period.

The daily consumption is 627.12Mwh corresponding to 26.13Mw for average power. The highest is 74.6Mw on 22:00 while the lowest 3.78Mw on 16:00. The ratio of highest and lowest is 19.7 times, this suggest it has a great potential for DSM using the evaluate method as Refs. [11].

According to the data provided by bureau of statistics [9-10], the electric energy demand of the domestic sector is approximately 29% of the total demand for Nanning (i.e. 3708 GW h of the 12643 GW h for 1-9 months in 2015). Therefore, the total electricity demand for electric bicycle will be 1.33% of total and 4.6% of the domestic consumption

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generation but also Furthermore, guiding users to avoid charging at peak time could not only reduce the marginal cost electricity for save money for consumers

IV. CONCLUSION

In this paper, a description of how to develop a time and space model to evaluate the energy demand of large-scale electric bicycle based on survey and Geographic information is presented.

Meanwhile, a method which could precisely deliver the energy demand on space was developed. The case study was based on Nanning, a city with 1.7 million electric bicycles in China.

The dataset includes 1574 data samples. The results show that the electric bicycle charging demand has the following characteristics:

The space model of Electric bicycle charging demand shows that the demand has a concentrated trend, in which it mainly concentrated in the urban area and decreased toward spreading suburbs. There is a large potential of business value for charging pipe managing company

Charging demand for electric bicycle will be 1.33% of total and 4.6% of domestic consumption for Nanning. It witnessed a maximum to minimum ratio about 20 times, which implies it has a great value for demand side management.

REFERENCES

[1] Beijing Beef information company China Electric Bicycle Industry Market Development Research Report [R],2012.

[2] Diana N, Sivakumar A, Pollak J W. Modelling electric vehicles use: a survey on the methods[J]. Renewable & Sustainable Energy Reviews, 2017, 68,pp.447-460.

[3] Michele DG, Elena P, Harald Scholz, Giorgio Martini. GIS-driven analysis of e-mobility in urban areas: An evaluation of the impact on the electric energy grid[J].Applied Energy,2014,124,pp.94-116.

[4] Daribi Z, Ferdowsi M. Aggregated impact of plug-in hybrid electric vehicles on electricity demand profile[J]. IEEE Trans Sustain Energy 2011,2,pp.501–8.

[5] Khan M, Kock Elman K M. Predicting the market potential of plug-in electric vehicles using multiday GPS data[J]. Energy Policy, 2012, 46(3),pp.225-233.

[6] Lei jigging et al. Calculation of electric vehicle load in Shenzhen based on Monte Carlo simulation in charging mode [C]. Proceedings of the 14th China

Association for Science and Technology Annual Conference 19: Electric Vehicle Charging and Discharging Technology Symposium, Shijiazhuang, 2012.

[7] NIE Xiao-jun, WEN Li-Zhong, WU Zhi-xing.Analysis of Electric Bicycle Market in Nanning [J],.Journal of Guangxi Teachers Education University(Philosophy and Social Sciences Edition).2010, 31, pp.11- 12,31

[8] Salameh ZM,CasaccaMa,Lynch WA.A mathematical model for lead acid batteries[J].1992,7(1),pp.93-98

[9] Guangxi Zhuang Autonomous Region Bureau of Statistics Page.; 2014 [accessed December 2016].

[10] China business information.< http://www.askci.com/news/chanye/2015/10/20/115756uupu.shtml>; 2016 [accessed December 2016]

[11] WANG Zhi-jie， LIU Shan-sham， XUE Song， ZENG Ming. Evaluation Model for Demand-Side Response Resource Value Based on Entropy and TOPSIS[J]. East China electricity power.2014,42(1),pp.143-149

[12] Koeltl R, Bauer D, Rudolf C. Travel behavior and e-mobility in Germany: Is the problem the driving range or costs or both?[J], Transportation Research Board-meeting. 2013.

[13] BAIDU map API.< http://api.map.baidu.com/lbsapi/cloud/index.htm>; 2016 [accessed December 2016]

[14] SANDELS C, FRANKE U, INGVAR N, et al. Vehicle to Grid Monte C Arlo Simulations for Optimal Aggregator Strategies [C].2010 International al Conference on Power System Technology, Oct- 24- 28, 2010, Hangzhou, Chime|ike, 2010,pp. 1–8.

[15] Hamasaki H, Shimamoto S. Kernel bandwidth optimization in spike rate estimation[J]. Journal of Computational Neuroscience, 2010, 29(1)