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# Verification and Analysis of Traffic Evaluation Indicators in Urban Transportation System Planning Based on Multi-Source Data– A Case Study of Qingdao City, China

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**ABSTRACT** In transport planning and urban planning, some standard traffic indicators are proposed to measure the level of urban transportation system. In early days, household traffic survey data is almost the only dataset in traffic indicators evaluation. However, numerous facts have proved that household traffic survey is expensive and dangerous. To our delight, with the development of social networking, mobile internet, electronic commerce and so on, various data are growing exponentially. The vast amount of data provides some new methods with better visualization, easier to understand and more efficient in measuring the level of urban transportation system. This paper tries to have an analysis on traffic evaluation indicators in transport planning based on the multi-source data, i.e., household traffic survey data, license plate recognition data, smart card data and location based service (LBS) data. Results show that household travel survey data has the strongest applicability, which can be used to all indicators calculation. However, due to the limitations of data content, only parts of indicators can be calculated based on license plate recognition data, smart card data and LBS data. After comparing with the standard indicators, the following results are obtained: (1) In Qingdao city, the well-run public transport system has not yet formed. Statistics found that the whole trip time of public transport in central urban area (full day) is 2.5 times that of individual motor vehicle, which don't meet the standard requirement (i.e., 1.5 times). (2) Parts of residents' travel distance is too far. Results show that the average travel distance of the top 15% travelers is about 3.3 times of the average travel distance of urban residents, which don't satisfy the standard requirement (i.e., 2.5 times). (3) Bus passengers and car users spend too much time on travelling compared other travel modes. Especially bus passengers need to spend 52 minutes to travel (the standard value is 40 minutes). (4) In Qingdao city, the proportion of public transport had been increasing. On the contrary, the non-motor travel has been decreasing.

**INDEX TERMS** Traffic evaluation indicators, multi-source data, average travel distance, average travel time.

## I. INTRODUCTION

Urban traffic system plays an important role in shaping urban spatial structure and pattern, guiding urban space expansion and promoting urban development. Comprehensive evaluation indexes of urban traffic are important in measuring the multivariate urban traffic system. Therefore, it is necessary to establish a scientific and reasonable index evaluation system to evaluate the current situation of urban traffic, determine the planning objectives, and have real-time evaluation of urban development. However, the sample size and dimension of the traditional data is small, which is difficult to meet the current requirements of urban comprehensive traffic development evaluation index. What's exciting is that with the rapid development of social networking, mobile internet, electronic commerce and so on, various data are growing exponentially.

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Take Baidu map as an example, in 2015, Baidu Map responded to 23 billion positioning requests every day. In 2017, it increased to 80 billion positioning requirements and covered 600 million devices. The vast amount of data provides some new methods with better visualization, easier to understand and more efficient in measuring the urban traffic conditions. Considering the richness and diversity of current data sources, this paper tries to have an analysis of traffic evaluation indicators on Qingdao city based on four kinds of data, i.e., household traffic survey data, license plate recognition data, smart card data and location based service (LBS) data.

### A. HOUSEHOLD TRAFFICSURVEY DATA

In the early stage of transport planning, large data sets were obtained by household traffic survey, which can be traced back to 1969, the U. S. Department of Transportation (USDOT) initiated an effort to collect detailed data on personal travel. Then it was continued in 1977, 1983, 1990, 1995, 2001 and 2009, respectively. As a classic method of traffic data collection, household traffic survey is common worldwide. It provides travel-related data such as travel mode, distance, departure time, arrival time, duration and purpose, and then combines the trip related information with demographic, geographic, and economic data for analysis. In general, household traffic survey data is used by policy makers, individual state DOTs, metropolitan planning organizations, industry professionals, and academic researchers for estimating and evaluating the extent and patterns of travel, planning new investments and the applications of data on trends in travel for policy and planning [1]. On the other hand, household traffic survey has encountered more and more challenge and doubts, such as sample sizes [2], [3], high cost and high risk [2], non-response rates [4], [5], inaccurate details of travel [6].

### B. LICENSEVPLA TERECOGNITION DATA

License plate recognition (LPR) data are new data sources that offer valuable information in gauging the traffic characteristic of urban arterials [7]. LPR systems are widely used in various traffic applications worldwide, such as traffic flow monitoring, automatic toll collection (ETC), parking lots, traffic law enforcement. For example, Qingdao city had built more than 8000 LPR cameras by the end of 2017. LPR systems offer a novel source of data that enable tracking the vehicles travel trajectory. According to Zhan *et al.* [7], LPR data have three unique characteristics: one is the accurate timestamp sequences for all vehicles; the second one is the available link travel time by comparing the timestamps of upstream and downstream intersections. The last one, due to LPR cameras record each lane of the arterial, detailed lane-based traffic information can be obtained. Considering the unique characteristics of LPR data, LPR data are widely used to estimate the link travel time and some other pioneering researches [7]–[9]. LPR systems have more obvious advantages in vehicle re-identification accuracy compared with other vehicle re-identification methods, e.g. dual loop detectors [10], [11], and vehicle signature [12]–[14]. The reason is that the re-identification of a vehicle under LPR technology focuses on unique license plate information, whereas in other methods the identifiers are restricted by various inaccuracies [7]. In a word, LPR data provide significant value in exploring pioneering researches for measuring urban traffic operational performance.

### C. SMART CARD DATA

Since the 1990s, with the rapid development of the Internet and mobile communication technologies [15], Smart card technology been gradually widely implemented in various fields all over the world, which includes health care, banking, government, human resources, transportation and so on. It is worth noting that in transportation field, the smart card is mainly used in public transit system accompanied with massive smart card data, which provide lots of precious opportunities for researchers. According to Pelletier *et al.* [16], studies on smart card data are grouped into three categories. One is strategic-level studies which involve long-term network planning, travel behavior analysis, and demand forecasting [15], [17]–[25]. At the tactical level, it is related to schedule adjustment, and longitudinal and individual trip patterns [26], [15], [18], [27]–[34]. The third is operational-level studies which involve supply-and-demand indicators, as well as to smart card system operations [21], [30], [35]–[38]. More specifically, according to Kim *et al.* [39], the smart card data are studied by scholars as a valuable source of data to analyze travel demand [30], origin-destination estimation [40], trip purpose inference [41], spatio-temporal patterns [42], service reliability [43], modal transfer behavior [44], passenger experience [45] and so on.

### D. LOCATION BASED SERICE (LBS) DATA

Various types of individual data originated from LBS technologies have been widely used to study urban characteristics [46]. As is well known, LBS data mainly comes from GPS. The application of GPS technology in travel surveys can be traced back to the late 1990s [47]. In the early stage of application, GPS surveys were mainly used to test the accuracy of traditional surveys (such as the household travel survey). Statistics found that the times and locations measured with GPS data loggers were more accurate [48]–[51]. It is worth noting that the GPS data is more promising when it is placed in a GIS application for further interpretation [52]–[55]. Considering issues of high expense, high-risk, low-response, data inaccuracy of the traditional surveys, GPS has the opportunity to supersede the traditional travel surveys and get more reliable and accurate data [56]. For the past decade, with the popularity of light-weight handheld GPS devices (such as the mobile phones), there has been a sharp increase in the use of handheld GPS data for having traffic survey and analysis worldwide [49], [57]–[67]. It is widely accepted that GPS can


**FIGURE 1.** Television propaganda and online questionnaire of the third household survey.

**TABLE 1.** Online-survey samples.

| OD Number | Family ID | Personal ID | Origin | | | Destination | | | Purpose | Trip mode | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Longitude | Latitude | Departure time | Longitude | Latitude | Arrival time | | Bus | Car | Taxi | Walk | Subway | Bike | Commuting Bus |
| 12 | 3 | 8 | 120.4378 | 36.1007 | 7:30 | 120.4144 | 36.1314 | 7:55 | Work | No | Yes | No | No | No | No | No |
| 13 | 3 | 8 | 120.4144 | 36.0857 | 17:30 | 120.3796 | 36.0875 | 17:45 | Shopping or F&B | No | Yes | No | No | No | No | No |
| 14 | 3 | 8 | 120.3796 | 36.0875 | 18:15 | 120.4378 | 36.1007 | 18:30 | Home | No | Yes | No | No | No | No | No |
| 15 | 3 | 9 | 120.4378 | 36.1007 | 7:20 | 120.4377 | 36.1008 | 7:25 | School | No | No | No | Yes | No | No | No |
| 16 | 3 | 9 | 120.4377 | 36.1008 | 16:00 | 120.4378 | 36.1007 | 16:05 | Home | No | No | No | Yes | No | No | No |
| 14 | 3 | 10 | 120.4378 | 36.1007 | 7:30 | 120.4335 | 36.1225 | 7:50 | Work | Yes | No | No | No | No | No | No |
| 15 | 3 | 10 | 120.4335 | 36.1225 | 17:00 | 120.4378 | 36.1007 | 17:40 | Home | Yes | No | No | No | No | No | No |
| 16 | 4 | 11 | 120.3988 | 36.0813 | 7:10 | 120.4118 | 36.1207 | 8:10 | Work | Yes | No | No | No | No | No | No |
| 17 | 4 | 11 | 120.4118 | 36.1207 | 18:00 | 120.3988 | 36.0813 | 19:10 | Home | Yes | No | No | No | No | No | No |
| 18 | 4 | 12 | 120.3988 | 36.0813 | 7:10 | 120.3976 | 36. 1027 | 7:56 | Work | No | No | No | No | Yes | No | No |
| 19 | 4 | 12 | 120.3976 | 36.1027 | 20:00 | 120.3988 | 36.0813 | 20:40 | Home | No | No | No | No | Yes | No | No |

As shown in table 1, every row is a trip (O-D). Family 3 has 3 members, i.e., 8, 9 and 10. Family 4 has 2 members, i.e., 11 and 12.

obtain more accurate data. However, the GPS survey also has some shortcomings. On the one hand, due to the limitation of communication technology, GPS has signal loss and signal noise. On the other hand, GPS data can't identify the mode of transportation and the purpose of travel.

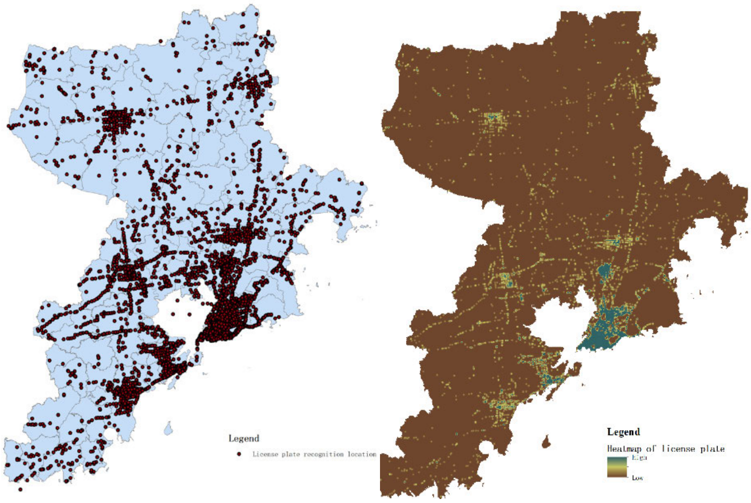
In recent years, with the completion of comprehensive transportation planning, Qingdao city conceptually realizes the sense of transportation system and gradually embraced it. The governments and municipal planners have made some works on transportation. Proponents of transportation development policies hope that urban transportation system will revitalize areas, promote the economic development, increase population density of urban areas and improve the quality of life. This hypothesis, however, has not been examined adequately in Qingdao city. The purpose of this study is to evaluate the changes and whether or not it is successful in achieving its aforementioned goals and objectives.

The paper is organized as follows. Section 2 presents the dataset used in our study. Section 3 presents the travel characteristics with different type of data. Section 4 discusses the rationality of evaluation indexes based on the multi-source data. Finally, some concluding remarks are presented in Section 5.

## II. DATASET DESCRIPTION

### A. RESIDENT SURVEY DATA

Qingdao city had three household traffic surveys in 2002, 2010 and 2016 respectively. Household traffic surveys in 2002 and 2010 are mainly the face-to-face home interviews. However, according to Stopher and Metcalf [68], face-to-face interviewing are expensive and dangerous. Meanwhile, with the tremendous increase of internet use and computer-mediated communication, A lot of researchers have a household traffic survey by using online surveys [69]–[74], which has low cost and high sampling rate compared to the face-to-face home interviews. Furthermore, it reduces researcher time and effort, such as accessing to individuals in distant locations, the ability to reach difficult to contact participants, and the convenience of having automated data collection [75]. In view of this, the household traffic survey of Qingdao city in 2016 mainly adopted the online-survey method. However, online-survey has its own shortcomings, such as the inaccurate departure and arrival times of the respondents, the travel time with errors, uncertainty over the validity of the data and sampling issues and so on [75]. Fig.1 gives the television propaganda pictures and online survey page of the third household survey in 2016.




(a) Location of license plate recognition systems (b)The heatmap of license plate recognition systems

**FIGURE 2.** Distribution of license plate recognition systems in qingdao city. License plate recognition data are from qingdao traffic police detachment.

As shown in table 1, besides acquiring the basic features of trips, such as departure and destination, travel mode, travel time and trip purpose, the questionnaire can also obtain the latitude and longitude information of departure and destination, which provides guarantee for the positioning of Origin-Destination (OD) pairs (Gao et al., 2019). The survey data are from Qingdao City Planning and Design Institute.

### B. LICENSE PLATE RECOGNITION DATA

Qingdao city had built more than 8000 LPR cameras by the end of 2017. It is worth noting that Qingdao's license plate recognition systems mainly concentrated in the four urban districts (i.e., Shinan District, Shibei District, Licang District, Laoshan District). Only a few are distributed in its peripheral areas, such as Pingdu city and Laixi city (Fig.2). Therefore, on some the specific paths which are distributed in the suburban districts, it is difficult to restore the travel trajectory completely through the license plate recognition systems. As shown in Fig.3, although license plate recognition systems can match some key points (the red points), it is still difficult to get the complete travel routes. On one hand, it can be attributed to the incomplete coverage of the license plate recognition systems. One the other hand, some data are missing because of the damage of camera (the green triangles in Fig. 3). In this paper, the license plate recognition data are from June 1, 2017 to June 7, 2017.

Table 2 shows the data content of the license plate recognition systems. As shown in Table 2, vehicle passing record includes the vehicle number plate, acquisition time of images, acquisition location number, etc. It filtrates the passing records of each vehicle. The database can match the geographic coordinate information according to the serial numbers of different collection locations. Table 3 and Table 4 gives location information sample and the data sample of the license plate recognition systems. As shown in Table 3, the location information of the license plate recognition systems mainly includes the location site, the longitude, the latitude and its jurisdictions. The license plate recognition data includes the license plate number, the acquisition time and site, equipment number and vehicle type (Table 4).

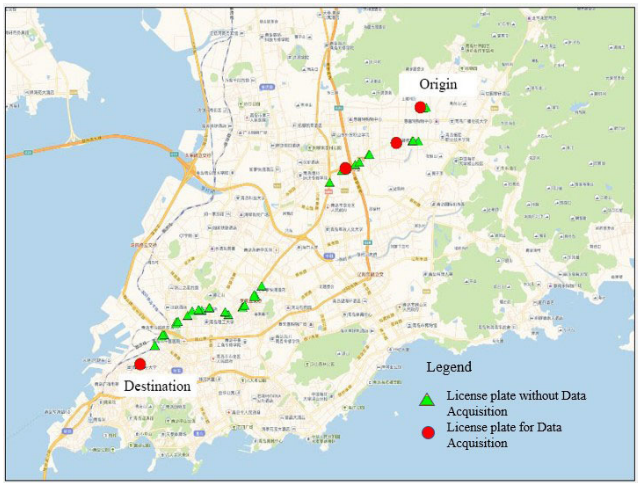



**FIGURE 3.** An example of data missing with license plate recognition system.

### C. SMART CARD DATA

Statistics show that there are 575 bus routes and more than 6900 stations in Qingdao city. Considering passengers swiping cards only when get on bus, the OD of bus trip can only be estimated approximately, which does not include the walking distance. The estimated OD distance would be shorter than the actual OD distance. In view of this, here the smart card data are only used to analyze the spatial distribution of OD. Table 5 gives the data sample of smart card in Qingdao city.

**TABLE 2. The license plate recognition data information.**

| | Field name | | Field name |
|---|---|---|---|
| Vehicle Passing Record | Automatic Numbering of Database | Database | Acquisition site number |
| | Number plates type | | Name of acquisition site |
| | License plate number | | Longitude of acquisition site |
| | Acquisition time | | Latitude of acquisition site |
| | Acquisition site number | | |
| | Name of acquisition site | | |
| | Acquisition Organ Number | | |
| | Snapshot type | | |
| | Equipment number | | |
| | Lane number | | |
| | Vehicle speed | | |

**TABLE 3. Location information sample of the license plate recognition systems.**

| Serial number | Location number | Location name | Longitude | Latitude | Jurisdictions |
|---|---|---|---|---|---|
| 1 | 010000205057 | 250 meters west of the parking line on Hangan Expressway (Wenzhou Road-Renmin Road) | 120.34921 | 36.09716 | 370203 |
| 2 | 010000205063 | 250 meters west of the parking line on Hangan Expressway (Shandong Road-Nanjing Road) | 120.37147 | 36.09524 | 370203 |
| 3 | 030000205037 | 250 meters west of the parking line on Hangan Expressway (Renmin Road-Anshan Road) | 120.35879 | 36.09464 | 370203 |
| 4 | 030000205039 | 250 meters west of the parking line on Hangan Expressway (Anshan Road-Shandong Road) | 120.36511 | 36.09499 | 370203 |
| 5 | 020000205047 | 200 meters west of the parking line on Hang an Expressway (Shandong Road-Harbin Road) | 120.37092 | 36.09528 | 370203 |
| 6 | 020000205049 | 250 meters west of the parking line on Hangan Expressway (Harbin Road -Fushun Road) | 120.37391 | 36.09542 | 370203 |
| 7 | 010000205066 | 250 meters west of the parking line on Hangan Expressway (Fushun Road -Nanjing Road) | 120.37768 | 36.09562 | 370203 |
| 8 | 030000205041 | 200 meters west of the parking line on Luoyang Road (Luyang Road -Anyang Road) | 120.37569 | 36.14302 | 370203 |
| 9 | 030000205045 | 250 meters west of the parking line on Luoyang Road (Anyang Road -Shangqiu Road) | 120.38163 | 36.14121 | 370203 |
| 10 | 030000205047 | 250 meters west of the parking line on Luoyang Road (Shangqiu Road -Zhoukou Road) | 120.38592 | 36.13991 | 370203 |

It includes the number of bus company, card number, card type, date, time and bus line number.

Fig.4 shows the bus passenger flow distribution of Qingdao city in peak hours. As shown in Fig.4, passengers are mainly concentrated in Shinan district, Shibei district and Licang district.

### D. LOCATION BASED SERVICE (LBS) DATA

Here Baidu map is used to obtain the LBS data. Baidu Map has a strong location capability. In 2017, Baidu Map responds to more than 80 billion location requirements per day. Its location equipment comes from 115,000 developers, 650,000 apps and websites. Location data's accuracy will be

**TABLE 4.** The data sample of license plate recognition systems.

| License plate number | Acquisition time | Equipment Number | Acquisition site | Vehicle type |
|---|---|---|---|---|
| 鲁 M4**2 挂 | 2017/6/6 4:45 | 611261001000 | The 9th middle school（S328) | 01(full-size) |
| 鲁 B7**8E | 2017/6/6 4:55 | 611301003000 | The intersection between Lijiang Road and Qingyunshan Road | 02(middle-size) |
| 鲁 DW**9H | 2017/6/6 4:55 | 102040237650 | The intersection between Yanshang Road and Jiuzhao Road | 02(middle-size) |

**TABLE 5.** The sample of bus smart card data.

| Bus company | Card number | Card type | Date | Time | Bus line |
|---|---|---|---|---|---|
| 11000001 | 2660100000083350 | 1000 | 20180506 | 210625 | 026 |
| 11000001 | 2660020010089110 | 200 | 20181024 | 110028 | 002 |
| 11000001 | … | … | … | … | … |
| 11000001 | 2660020010069700 | 100 | 20171018 | 221757 | 405 |

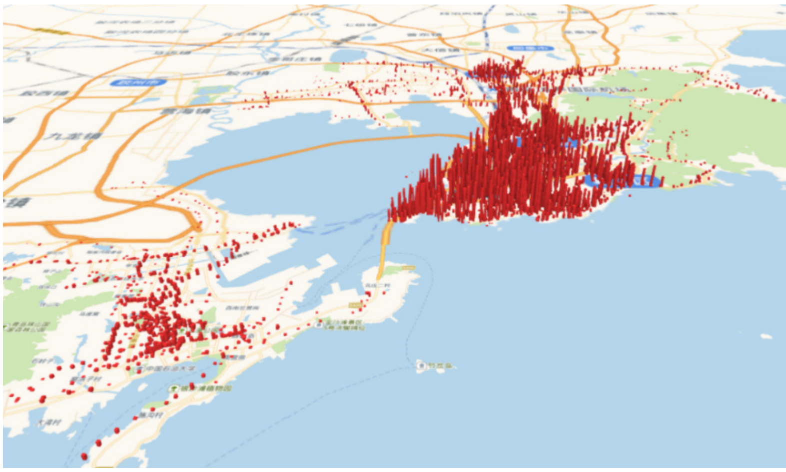


**FIGURE 4.** Bus passenger flow distribution of qingdao city in peak hours. The smart card data are from qingdao public transportation group.

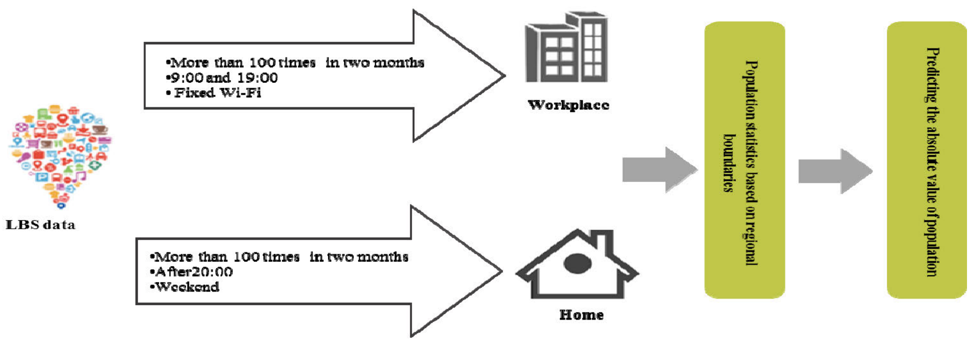



**FIGURE 5.** Population identification roadmap.

more than 85% by model training and machine learning [76]. Fig.5 gives the roadmap of population identification.

(1) Appearing more than 100 times in the same place in two months;

(2) The occurrence time is concentrated between 9:00 and 19:00;

(3) The Wi-Fi (Wireless Fidelity) of the connection is fixed.

**TABLE 6.** The requirements of 85% citizens' commuting time.

| Population size (million) | ≥ 5 | 1~5 | ≤ 1 |
|---|---|---|---|
| Commuting time (min) | ≤ 40 | ≤ 30 | ≤ 25 |

**TABLE 7.** The requirements of 85% citizens' commuting distance.

| Population size (million) | ≥ 5 | 3~5 | 1~3 | 0.5~1 | ≤ 0.5 |
|---|---|---|---|---|---|
| Commute distance (km) | ≤ 8 | ≤ 6 | ≤ 5 | ≤ 4 | ≤ 3 |

Similarly, the place of residence could be determined if the location meets following three conditions:

(1) Appearing more than 100 times in the same place in two months;

(2) The occurrence time is concentrated after 20:00;

(3) Most weekends are located at this place.

We can obtain the LBS data by this contact page: https://huiyan.baidu.com/contact.html.

## III. TRAVEL INDICATORS VERIFICATION BASED ON MULTI-SOURCE DATA

In order to guarantee the sustainable development of urban transportation system, support the efficient operation of cities and standardize the urban transportation system planning, China construction administration set ***Standards for Urban comprehensive Transportation System planning***in 2018. It gives some target requirements from the spatiotemporal perspectives. Specifically, some of them can be tested by the above four kinds of data, which are listed as follows:

(I) In large cities with a population of more than one million, the average travel time of public transportation should be controlled within 1.5 times the average travel time of individual motor vehicles in peak hours.

(II) 85% of commuters' average one-way travel time should be satisfy the following requirements in different cities with different population sizes (As shown in Table 6).

(III) In the cities with a population of more than one million, the average value of the top 15% travel distance in the urban concentrated construction area should not exceed 2.5 times the average travel distance of the urban residents.

(IV) Trip distance should satisfy the following requirements in different cities with different population sizes (As shown in Table 7).

(V) In the cities with a population of more than one million, the number of public transportations, of bicycle travelers and walkers should account for at least 75%.

In the next section, the five indicators will be evaluated based on the four kinds of data which are mentioned in the previous section. According to the 6th national population census in 2010, there are 8715100 people in Qingdao city. Therefore, Qingdao city will implement the criteria of more than or equal to 5 million population size.

### *A. TRAVEL INDICATORS VERIFICATION BASED ON HOUSEHOLD TRAFFIC SURVEY DATA AND ELECTRIC MAP API*

According to the third household traffic survey data, as shown in table 8, in 2015, public transportation, bicycle travelers and walkers only account for 66.9%, which is less than 75%. From 2002 to 2015, the proportion of public transport had been increasing. On the contrary, the non-motor travel had been decreasing. Unfortunately, the ratio of public transportation, bicycle travelers and walkers had been gradually decreasing from 2002 to 2015 (i.e., 79% in 2002, 67.4% in 2010 and 66.9% in 2015).

Although household traffic survey could obtain some data we need, such as the information of Origin-Destination (OD), travel mode and travel time, it is difficult to acquire the trip routes information. At the same time, the trip time and trip distance are usually inaccurate. What's exciting is that electric map application program interface (API) (e.g., Google Maps, Apple Maps, Baidu Maps, Auto Navi Maps and so on) could offer the accurate trip route and time information, which remedies the household traffic survey's defect (Gao *et al.*, 2019). Table 9 gives data sample of Baidu Maps Web API.

As shown in Table 9, for one OD, it recommends 5 routes. For bus travelers, it includes the route length, travel time, initial walk time, initial walk time, travel distance by bus, travel time by bus, arrival walk distance and arrival walk time and so on. Here household traffic survey data and Electric map API data are used to have a travel indicators verification. OD pairs, trip mode and travel purpose are from household traffic data source. Trip route and time information are from Electric map API.

Statistics found that in peak hours, the average travel time of public transportation is 2.5 times individual motor vehicle, which is higher than the indicator (1.5 times). As shown in Fig.6, car travel time is centralized between 10-40 minutes. However, the distribution of bus travel time is uniform. Combing household traffic survey data and Electric map API data, Gao *et al.* (2019) gave the trip distance distribution and trip time distribution with 6 different purposes (Fig. 8). As shown in Fig.8(b), the average commuting time is 30.54 minutes, which shows that 85% of commuters' average

**TABLE 8.** The composition of residents' travel mode in 2002, 2010 and 2015.

| - | Bus | Taxi | Metro | Car | Regular bus | Motorcycle | Non-Motor | Others |
|---|---|---|---|---|---|---|---|---|
| 2002 | 19.6% | 6.5% | - | 10.6% | 4% | 8.8% | 48.9% | 1.6% |
| 2010 | 22.1% | 6.3% | - | 28.4% | 2.7% | 3.1% | 36.3% | 1.1% |
| 2015 | 24.2% | 5.7% | 0.2% | 31.3% | 2.5% | 1.1% | 34.3% | 0.8% |
| D-value | 2.10% | -0.60% | 0.20% | 2.90% | -0.20% | -2.00% | -2.00% | -0.30% |

**TABLE 9. Data sample of baidu maps web API.**

| OD Number | Recommended Travel Routes | Length (m) | Travel time(s) | Initial Walk Distance (m) | Initial Walk time (s) | Travel distance by bus | Travel time by bus | Arrival walk distance (m) | Arrival walk time (s) |
|---|---|---|---|---|---|---|---|---|---|
| 8 | 1 | 10685 | 3286 | 164 | 131 | 10202 | 2300 | 319 | 255 |
| 8 | 2 | 10580 | 3782 | 383 | 306 | 229 | 183 | 255 | 204 |
| 8 | 3 | 12363 | 4193 | 386 | 308 | 10890 | 2415 | 1087 | 869 |
| 8 | 4 | 11989 | 4145 | 179 | 143 | 10447 | 2311 | 1363 | 1090 |
| 8 | 5 | 11183 | 4127 | 143 | 114 | 363 | 290 | 323 | 258 |

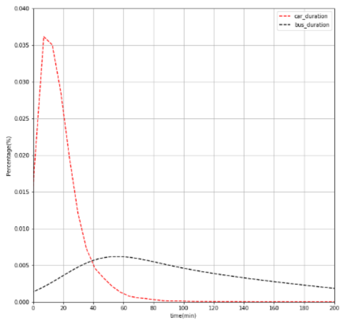


**FIGURE 6. Travel time distribution of bus and car.**

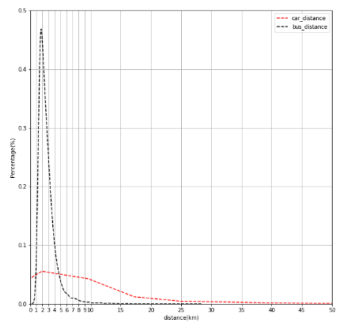
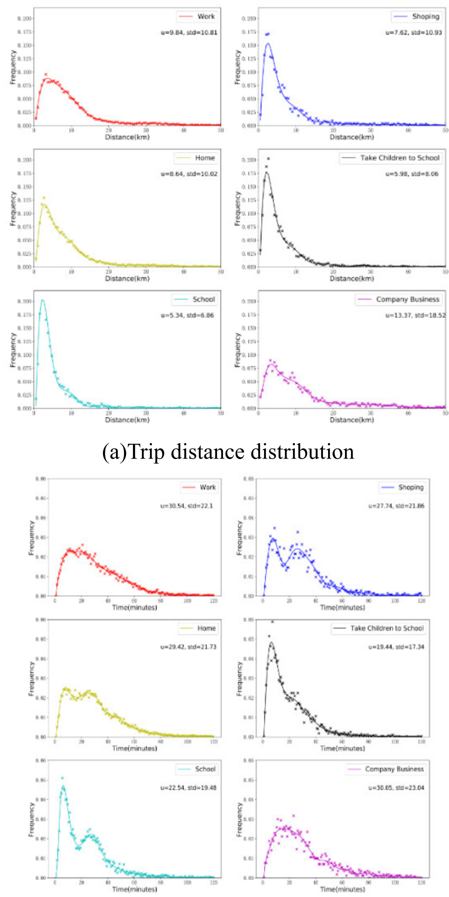


**FIGURE 7. Travel distance distribution of bus and car.**



(a)Trip distance distribution

(b) Trip time distribution

**FIGURE 8. Trip distance and trip time distribution with 6 travel purposes.**

one-way travel time is shorter than 40 minutes. According to Figs. 7 and 8 (a), the average commuting distance is 9.84 kilometers, which is higher than 8 kilometers. The 85% of commuters' average travel distance is 5.51 kilometers, which is shorter than 8 kilometers. The top 15% of commuters' average travel distance is 31.1 kilometers, which is 3.16 times the average commuting distance (9.84 kilometers). It doesn't satisfy the requirement, i.e., not exceed 2.5 times the average commuting distance.

### B. TRAVEL INDICATORS VERIFICATION BASED ON LICENSE PLATE RECOGNITION DATA AND SMART CARD DATA

#### 1) TRAVEL INDICATORS VERIFICATION BASED ON LICENSE PLATE RECOGNITION DATA

Due to the limitation of the license plate recognition data itself, the mode ratio of the public transportations, bicycle travelers and walkers can't be obtained. Here only indicators (II), (II) and (IV) are acquired.

Car trajectory can be obtained by analyzing the records of license plate recognition systems. Statistics found that the commuting time of 85% of the cars in Qingdao is 41 minutes, which can't meet the standard requirements (40 minutes) in the ***Standards for Urban comprehensive Transportation System planning***. As shown in table 10, the top 15% travel distance is 3.3 times the average travel distance of the urban residents, which is also higher than the

**TABLE 10. Indicators based on license plate recognition data.**

| | Distance (km) | Time (min) |
|---|---|---|
| Mean | 13.71 | 22.1 |
| Std | 13.47 | 15.3 |
| 25% | 4.6 | 11.2 |
| 50% | 8.82 | 18.5 |
| 85% | 18.12 | 41 |

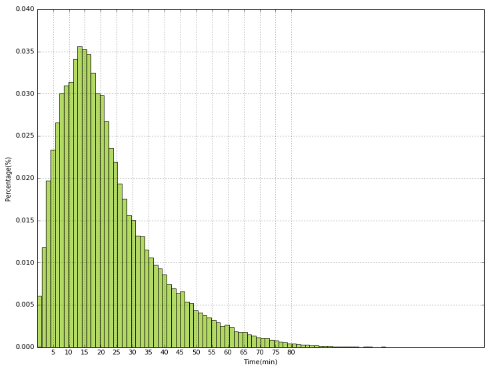


**FIGURE 9. Residents' travel time distribution in early peak.**

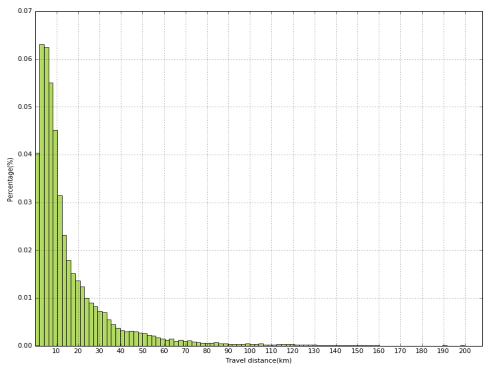


**FIGURE 10. Residents' travel time distribution in early peak.**

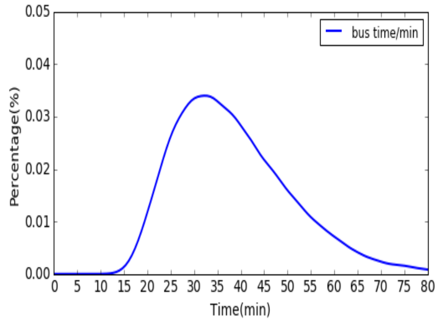



**FIGURE 11. Bus travel time distribution in morning peak.**

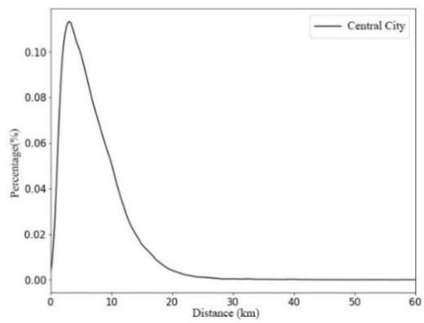



**FIGURE 12. Bus travel distance distribution in morning peak.**

standard requirements (2.5times). The average travel distance is 13.71 kilometers, which is higher than 8 kilometers.

Figs.9 and 10 give the histogram of travel time and distance distribution of residents in early peak respectively. As shown in Fig.9, 13.5 minutes has the highest percentage. Residents' travel time is concentrated between 5 minutes and 45 minutes. As shown in Fig.10, most residents' travel distance are no more than 30 kilometers. 4 kilometers has the highest percentage.

### 2) TRAVEL INDICATORS VERIFICATION BASED ON SMART CARD DATA

Smart card data only record the bus travelers' information. Therefore, only the indicators of bus travelers are calculated. Based on 120000 smart card data in central urban area, the travel time and distance distribution of each OD is obtained. As shown in Fig. 11, the 85% commuting time of bus passengers is 52 minutes, which is higher than the standard requirements (41minutes). Statistics found that the 85% commuting distance of bus passengers is 5.54 kilometers (Fig.12) which satisfy the requirement (8 kilometers). The average commuting time of bus passengers is 54 minutes and the average commuting distance of bus passengers is 6.98 kilometers.

## *C. TRAVEL INDICATORS VERIFICATION BASED ON LBS DATA*

Considering the limitations of LBS data, only the indicators (II), (II) and (IV) are calculated. Statistics found that the 85% average commuting time is 38 minutes, which meets the standard requirements (less than 40 minutes). 15% of the largest travel distance is 3.3 times of the average travel distance of urban residents, which is higher than the standard requirements (2.5 times). The 85% commuting distance is 7.4 kilometers, which meets the standard requirements (less than 8 kilometers). In order to describe the distributions of

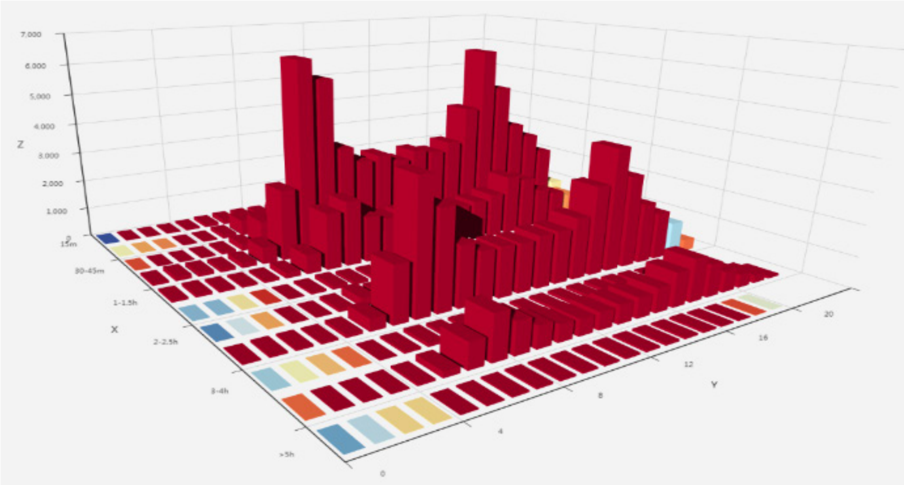



**FIGURE 13.** Distribution of travel time of urban residents on weekdays.

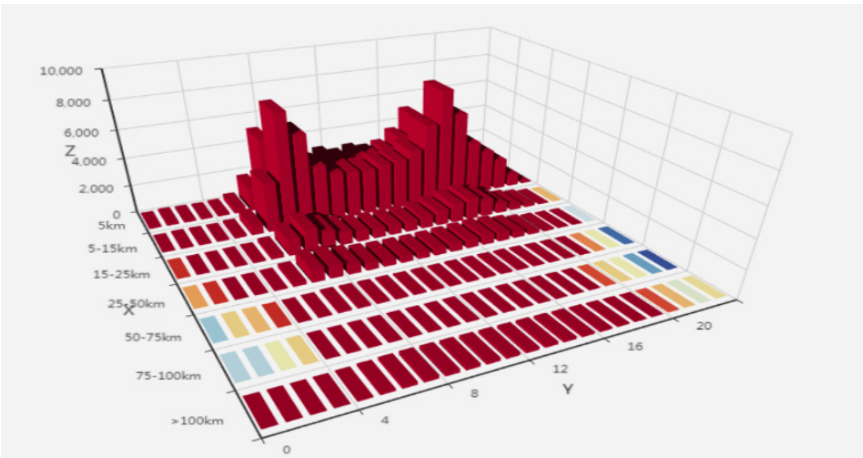



**FIGURE 14.** Distribution of travel distance of urban residents on weekdays.

**TABLE 11.** Indicator comparison with different data type.

| | Indicator (I) | Indicator (II) | Indicator (III) | Indicator (IV) | Indicator (V) |
|---|---|---|---|---|---|
| Standard | ≤ 1.5 times | ≤ 40 minutes | ≤ 2.5 times | ≤ 8 kilometers | ≥ 75% |
| Household travel survey data and Electric map API | 2.5 times | 30.54 minutes | 3.16 times | 5.51 kilometers | 66.9% |
| License plate recognition data | - | 41 minutes | 3.3 times | 13.71 kilometers | - |
| Smart card data | - | 52 minutes | - | 5.54 kilometers | - |
| LBS data | - | 38 minutes | 3.3 times | 7.4 kilometers | - |

travel time and distance more vividly, the 3-D histograms are given in Figs. 13 and 14. As shown in Fig.13, most travelers' duration are concentrated within 1.5 hours. Some travelers would spend 3 hours or more. Different from the travel time, the distribution of travel distance is more centralized, more than 95% of travelers travel no more than 15 kilometers (Fig.14).

### D. INDICATOR COMPARISON WITH DIFFERENT DATA TYPE

In order to analyze the applicability of the aforementioned four kinds of data in traffic indicator evaluation, table 11 is made to have an indicator comparison. As shown in table 11, household travel survey data and electric map API have the has the strongest applicability, which can be used to all indicators calculation. Here license plate recognition data only record car's information and smart card data only record the bus passenger information. Therefore, indicators (I) and (V) can't be calculated based on license plate recognition data and (I), (III) and (V) based on smart card data. Considering the characteristics of license plate recognition data and smart card data, the two kinds of data can be integrated together and then have an indicator evaluation in future research. For LBS data, due to it can't identify the travel mode, indicators (I) and (V) can't be calculated. From table 11, we can also find that under the same indicator, different types of data have different indicator values. For indicator (II), two datasets meet the standard, i.e., household travel survey data and electric map API data and LBS data. Due to smart card data only stands for bus passengers, its 85% of commuters' average one-way travel time (52minutes) is longer than the standard travel time (40 minutes), the same as license plate recognition data. Therefore, household travel survey data and LBS data have better applicability. For indicator (III), the three kinds of data have the similar value (about 3.3 times). As shown in the fifth column of table 11, indicator (IV) could also verify the strong applicability of household travel survey data and electric map API data and LBS data.

## IV. CONCLUSION

This paper has an analysis on traffic evaluation indicators based on four kinds of data, i.e., household traffic survey data, license plate recognition data, smart card data and location based service (LBS) data. In the analysis, different data show different adaptability. Results find that household travel survey data has the strongest applicability, which can be used to all indicators calculation. Due to the limitations of data content, only parts of indicators can be calculated based on license plate recognition data, smart card data and LBS data. Another discovered that under the same indicator, different types of data have different indicator values, i.e., some datasets meet the standard requirement while others do not. The most obvious is that the household travel survey data and LBS data meet the indicator (II), while the smart card data and license plate recognition data are not satisfied. It found that in Qingdao city, most standard indicators are not satisfied, which are listed as follows:

(1) In Qingdao city, the well-run public transport system has not yet formed. Statistics found that the whole trip time of public transport in central urban area (full day) is 2.5 times that of individual motor vehicle, which don't meet the standard requirement (i.e., 1.5 times).

(2) Parts of residents' travel distance is too far. Results show that the average travel distance of the top 15% travelers is about 3.3 times of the average travel distance of urban residents, which don't satisfy the standard requirement (i.e., 2.5 times).

(3) Bus passengers and car users spend too much time on travelling compared other travel modes. Especially bus passengers need to spend 52 minutes to travel (the standard value is 40 minutes).

(4) In Qingdao city, the proportion of public transport had been increasing. On the contrary, the non-motor travel has been decreasing.

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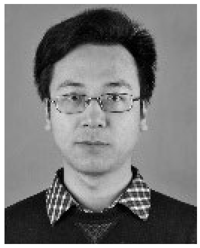

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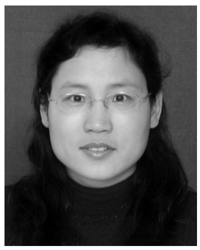

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