The Potential of Carbon Emissions Reductions of Public Bikes

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Abstract: The reduction of carbon emissions has become a heated background topic in the context of climate change. This paper estimates the potential for carbon reduction from the use of public bikes, on the basis of a travel mode choice model and a carbon emission calculation model. A probability model for the travel mode choice is built to predict travel demands of different modes, and is based on the Logit-based stochastic user equilibrium model. According to this, the generalized travel cost of choosing to walk increases with distance, but the cost of choosing a taxi decreases with distance. When the trip distance is 1.4 km, the walk cost equals to that of the taxi, while if the trip distance is smaller than 1.4 km, the probability of the walk is larger than of a taxi, and vice versa. The case of Ningbo is analyzed. Based on the monthly travel data, the travel characteristics of the public bikes are first analyzed; these indicate that the medium travel distance is 1.44 km, and that the number of trips less than 1.6 km accounts for 70% of all trips. This reveals that the public bike trips are mainly short-distance and in workday rush hour. The related carbon emission reductions of Ningbo on average are 1.97 kg/person and 1.98 kg/km, and the reductions are positively linearly related to the average hourly total turnover rate, which means the turnover rate is a great parameter to reflect the capability of carbon emission reductions.

Keywords: public bike; carbon emissions; environmental benefits; travel mode

1. Introduction

In recent years, the reduction of carbon emissions has become the focus of attention of the world. Local governments in many countries are trying their best to reduce carbon levels. As early as 2014, in the China-US Joint Announcement on Climate Change, China first put forward its planned target for carbon peak by 2030. In September 2020, at the General Assembly of United Nations, President Xi Jinping promised the world that China would increase its national independent contribution to efforts to tackle climate change and try to achieve carbon peak by 2030 and carbon neutrality by 2060. Transport accounts for 40% of global emissions, 72% of which comes from road transport [1]. The transportation sector is the second-highest sector for energy-related CO₂ emissions worldwide because the transport industry is heavily dependent on fossil fuels [2]. In 2015, China’s transportation sector produced 843.9 million tonnes of CO₂, of which 698.3 million tonnes originated from road traffic, accounting for 82.7% of the total transportation emission, and these emissions are increasing annually [3–5]. Therefore, China’s road traffic carbon emission status and mitigation measures have a great impact on China’s ability to see its carbon peak in 2030, as well as the trend after the peak.

The main measure to reduce road transport carbon emissions is vehicle electrification, which means replacing fuel-powered vehicles with electric vehicles. However, there are still societal concerns regarding the environmental benefits of the technologies involved in electric vehicles (EVs) and the extent to which new energy options and vehicles benefit the Carbon Neutral Plan. The impact of EVs on emission reductions have been widely debated and the conclusions of existing studies are still controversial. Some studies show that EVs with clean energy generation of the electricity are an optimal choice, which could decrease the environmental impact of private vehicles and mitigate climate change [6–9]. Some
studies present different findings. Lai Yang et al. indicated that, compared with internal combustion engine vehicles (ICEV), plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV) were found to reduce the emissions of CO$_2$, VOCs, and NO$_X$, but to increase the emissions of PM2.5 and SO$_2$ [10]. Huo et al. thought that BEV could not reduce CO$_2$ emissions [11], and Petrauskiene et al. reported in 2015 that emissions associated with BEV generate 26% more GHG than those of ICEV fueled with petrol [12]. Meanwhile, Yuan et al. reported that only short-driving-range (<250 km) BEV with low driving speeds (<80 km/h) can reduce CO$_2$ emissions compared with ICEV [13]. Some studies show the potential reductions from transportation structure transfer is equivalent to that vehicle electrification [3], in that if policy makers focus only on promoting new energy vehicles, they will probably fail at the same time to respond to the urgent need for carbon reduction. On the one hand, this is because a long time is needed to achieve full vehicle electrification. On the other hand, it is due to the new energy vehicles not being fully zero carbon, since the process of extracting the raw materials for batteries, manufacturing and liquidation still produce carbon emissions. Therefore, to encourage people to travel by bikes and public transport, rather than private vehicles, is the better way to reduce carbon emissions.

There is no doubt that public bike systems are a cleaner low-carbon travel mode, and there are no vehicular traffic problems, such as parking difficulties, traffic congestion etc. Some studies have confirmed that the environmental benefits of travel by public bikes exceed its health benefits [14–16]. It has been confirmed from previous studies that bike travel can reduce carbon emissions directly and indirectly [17–19], while the effects of shared bikes on reducing carbon emissions vary according to different scenarios. The promotion of public bikes plays a very important role in increasing the amount of travel by bikes, in meeting the needs of the transient population, and in reducing the environmental impact of the motorized transportation system. Moreover, the sharing travel modes become more and more popular because of their convenience, low cost, low carbon emissions and environmental pollution, etc. [20,21].

In this paper, we will analyze the environmental benefits of travel by public bikes. For this purpose, some measurement models of environmental benefits from public bikes have been developed, for which there are two main approaches. The first is to undertake a life cycle assessment considering carbon emissions generated and reduced over the entire life cycle of public bikes [1,22–24]. The second is to estimate the capability of reducing carbon emissions by reducing demand as travel is shifted to bikeshare [25–28]. The first approach or method considers carbon emissions more comprehensively, and the second analyzes the carbon emission reductions of bikeshare usage more deeply. However, in terms of travel mode replacement and apportionment, both methods are arbitrary, and the prediction is not sufficiently accurate. The method in this paper eliminates this limitation by introducing a more consistent model, the probability model of travel mode choice, which is a Logit-based stochastic user equilibrium model. Taking Ningbo as an example, this paper explores and displays the temporal and spatial characteristics of travel by public bikes in Ningbo based on abundant trip data, and quantifies the environmental benefits by using a mode choice model and environmental benefit model.

This paper is composed of the following parts: Section 2 provides a brief overview of the relevant literatures. Section 3 presents the models of travel mode choice and environmental emissions. Section 4 introduces the study area and the method of data preprocessing, the space and time characteristics of public bikes, and quantitative reductions in emissions of carbon and other pollutants. Section 5 discusses conclusions and implications.

2. Literature Review

The public bike first appeared in the Netherlands in 1967, and the intelligent operation and management system of the public bike entered China in 2007. Beijing is the first city to implement public bikes. After that, public bikes were implemented in many cities across China. The bike-sharing program has experienced a boom since 2015 in many countries. There were more than 400 cities in China which had built and implemented public bike
systems by December 2016, and the number of bikes in operation had reached 890,000 [29]. However, the expansion of the shared bike business may lead to a negative impact. In recent years, the wave of bike-sharing in China has passed, and some bike-sharing companies have withdrawn from the market. The public bike service has been stopped in Guangzhou, Wuhan, Handan, Xiamen, and Hohhot etc., and many cities report a low usage rate of public bikes.

There is a large number of studies on carbon emission reductions from bike shares. Some studies analyze the policy and system of the carbon emissions trading market and their impact on bike transportation [30]; some studies estimate the amount of carbon emissions from bike shares [1,22–24]; others analyze the theory of the mechanism of carbon emission reductions from bike shares [26]; and yet other studies analyze the carbon emission reduction effect of the e-bike [27,28].

Baek Woohyun reviewed the recent carbon emissions trading market literature, and conducted a SWOT analysis on the bike transportation system in Korea and a policy topology analysis [30]. Based on the literature reviews and SWOT analysis, a new bike transportation activation policy and a business model including bus, subway, T-money and bike riders to give some incentive was proposed, which were showed effective and reasonable.

Xiao GuangNian et al. calculated the carbon emissions generated and reduced over the entire life cycle of public bikes based on the life cycle theory [23]. It was found that when the average daily turnover rate of public bikes is 1.874 times/bike, the average daily travel distance is 2.150 km, and the damage rate increases by 2.5% per month; each public bike needs approximately 7 months to reach the carbon balance, then the use of public bikes causes a net reduction in carbon emissions; however, the carbon emissions once again exceed the emission reductions after approximately 29 months of using public bikes. D’Almeida Lea et al. undertook a life cycle assessment (LCA) of a public self-service bike sharing system in the city of Edinburgh, UK, modelling the production, operation and disposal elements of the system [1]. The results showed that the bike-sharing scheme can save carbon dioxide emissions, and the overall emissions impacts of the scheme are critically dependent on how public transport providers respond to reductions in demand as users shift trips to bikeshare, since this mostly involves the transfer from walking and public transport, not from private car. Zhang Yongping et al. quantitatively estimated energy use and carbon dioxide (CO₂) and nitrogen oxide (NOₓ) emissions of bike sharing in Shanghai using big data techniques from a spatiotemporal perspective [24]. The results showed that the bike sharing in Shanghai saved 8358 tonnes of petrol and decreased CO₂ and NOₓ emissions by 25,240 and 64 tonnes in 2016. Chen Jingrui et al. used a life cycle carbon emission assessment to calculate an emission reduction threshold for the bike-sharing industry [22]. The results showed that the whole life cycle carbon footprint is 34.56 kg CO₂/bike, and if a bike is deposited directly in a landfill, it will take 31 years to degrade. Therefore, each bike used at least 686 days to achieve a net positive reduction in emissions. Wang Sishen et al. compared the carbon footprint of two transportation modes in campus transit—bus and bike-share systems—using a life-cycle assessment (LCA) [31]. The results showed that the majority of CO₂ emissions and energy consumption comes from the raw material stage of the bike-share system and the operation stage of the campus bus system. The CO₂ emissions and energy consumption of the current campus bus system are 46 and 13 times that of the proposed bike-share system, respectively. Cao Yijie et al. analyzed the factors affecting the environment from shared bikes and the usage of bikes [32]. The results showed that the influencing extent of factors on CO₂ emission reduction is in the following order: riding distance > proportion of registered users > usage rate of shared bikes. Rojas-Rueda D et al. estimated the health risks and benefits of mode shifts from car to cycling and public transport in the metropolitan area of Barcelona, Spain, by conducting a health impact assessment (HIA), which created 8 different scenarios of the replacement of short and long car trips by public transport and/or bike [18]. The results showed that the carbon dioxide reduction by shifting from car to other modes of transport (bike and public transport) in Barcelona metropolitan area was estimated to be 203,251 t/CO₂ emissions per
year. Gilderbloom John et al. reported the results of a survey of 2032 responses from faculty, staff, and students of a car-dependent, downtown university [33]. The results informed potential savings and economic benefit calculations that can be achieved from bicycle infrastructure investments and anticipated redistributed spending patterns. Lai Ruxin et al. also used Life cycle assessment (LCA) as a method to analyze the environmental impact of free-floating bike sharing (FFBS) [34]. The results showed the trip mode of connecting public transport with FFBS could better replace the motorized transport trip and generate better low-carbon benefits with savings of 300.718 g CO$_2$-eq/p km.

Yongji Jia et al. established the mixed integer programming model with the objective of minimizing the total rebalancing cost of the mixed fleet, which is a fleet of electric vehicles and internal combustion vehicles along with traffic restrictions to traditional vehicles [25]. Then, a simulated annealing algorithm enhanced with variable neighborhood structures is designed and applied to a set of randomly generated test instances. Li Huimin et al. developed a theoretical model for the emission reduction mechanism of a bike-sharing system, and analyzed the shared bike’s emission reduction benefits based on China’s case [26]. It was shown that riding the shared bike for 1 km can reduce emissions by 9.54 g CO$_2$. The study identified four key variables for determining the emission reduction contribution of bike-sharing, namely, the travel distance, turnover rate, lifespan and replacement rate. Bigazzi Alexander et al. investigated the joint consideration of energy expenditure, air quality, and safety concerns by cyclists, and their relationships with cycling frequency [35]. Model results show that traffic safety and air pollution risks are perceived differently by cyclists, which has implications for modeling urban cycling behavior in the context of evolving motor vehicle fleets. Hongliang Ding et al. studied the effect of the ultra-low emission zone (ULEZ) on the demand for public bike sharing in London, based on the bike usage data from 699 bike docking stations between May 2019 and October 2019 [36]. Results indicate that bicycle demand increased significantly (27.9%) after the introduction of ULEZ. In addition, increases in bicycle demand were more profound for short (within 15 min, 25.3%) and intermediate (15 to 30 min, 28.8%) trips.

McQueen et al. estimated e-bike impacts on greenhouse gas emissions [28]. A mode replacement model was adapted and augmented to consider the case of Portland. It was estimated that for 15% of e-bike person miles traveled (PMT) mode share, car trip mode share could be reduced from 84.7% to 74.8%; furthermore, carbon dioxide (CO$_2$) emissions from passenger transportation could be reduced by 12% after accounting for e-bike emissions from electricity generation and induced e-bike trips. An individual e-bike could provide an average reduction of 225 kg CO$_2$ per year. Liu Yixiao et al. established a set of methods to use the data of existing docked bike sharing systems to pre-estimate the emission reduction effects of future docked electric bike sharing system [27]. They found that the emission reduction caused by the substitution effect after upgrading the docked bike sharing system to the docked electric bike sharing system is 4.19 times that of the original, and the reduction in emissions caused by its substitution effect on taxis is three times that of the original. If 1% of the permanent residents of Nanjing change their commuting vehicles from cars to electric bicycles, the one-way emission reduction will exceed 9.55 tonnes of carbon dioxide. Philips Ian et al. estimate the maximum capability to reduce CO$_2$ by substituting private car travel with e-bike [37] to be 24.4 MTCO$_2$ p.a. (per annum) in England, and CO$_2$ saving capability per person and per small area are highest for residents of rural areas.
3. Methodology

3.1. Probability Model of Travel Mode Choice

The probability model of travel mode is a Logit-based stochastic user equilibrium model for mode choice [38], which takes the minimization of the travel cost as the objective. The model is formulated as follows:

$$
\min Z(q) = \sum_{r \in R} \int_0^{q_r} c_i^r(x) \, dx + \frac{1}{\theta} \sum_{i \in I} \sum_{r \in R} q_i^r \ln q_i^r
$$

s.t.

$$
\sum_{i \in I} \sum_{r \in R} q_i^r = Q_w, \forall w \in W
$$

$$
q_i^r \geq 0, \forall r \in R, i \in I
$$

where, $Z(q)$ is the objective function, $q_i^r$ is the traffic flow of the travel mode $i$ along the route $r$, $c_i^r$ is the generalized travel cost of the travel mode $i$ along the route $r$, and $W$ is the set of the routes of OD pair $w, R$ is the set of the routes of all of the OD pairs, $\theta$ is the traveler perception degree of impedance, which is inversely proportional to the perception error, $I$ is the set of travel modes, and $Q_w$ is the traffic demand of OD pair $w$.

The travel cost function consists of a deterministic term and the stochastic error, which is shown in Formula (2). The stochastic error term follows the Gumble distribution. The deterministic term of the generalized travel cost of mode $i$ includes time cost ($t_i^r$) and economy cost ($e_i^r$), which apply $\delta_1$ and $\delta_2$ as penalty coefficients. The penalty coefficients are related with an individual’s physical fatigue, psychological pleasure and other subjective feelings. The generalized travel cost model is formulated as follows:

$$
c_i^r = \delta_1 \cdot t_i^r + \delta_2 \cdot e_i^r + \xi_i^r
$$

where, $c_i^r$ is the generalized travel cost of the travel mode $i$ along the route $r$, $t_i^r$ is the time cost of the travel mode $i$ along the route $r$, $e_i^r$ is the economy cost of the travel mode $i$ along the route $r$, and $\xi_i^r$ is the stochastic error of the travel mode $i$ along the route $r$.

Because the bike travel is usually within a short distance, the shorter the travel distance is, the more the money is lost psychologically. Therefore, the penalty coefficient of economic cost is inversely related with the trip distance, which is:

$$
\delta_2 = \gamma_2 / d_r
$$

Based on the Formulas (1) to (4), the travel cost model is:

$$
c_i^r = \gamma_1 \left( \frac{d_r}{d_{\min}} - 1 \right) \frac{d_r}{v_i} + \gamma_2 \cdot e_i^r + \xi_i^r
$$

where, $\gamma_1, \gamma_2$ are the estimated parameters, $d_r$ is the trip distance of route $r$, $v_i$ is the average travel speed of travel mode $i$, $d_{\min}$ is the minimum threshold for walking, i.e., people would choose to walk if the trip distance is shorter than this threshold.

Applying the Lagrange relaxation to the probability model of travel mode choice, the Lagrange function can be obtained as follows:

$$
L = Z + \sum_{w \in W} \mu_w \left( Q_w - \sum_{i \in I} \sum_{r \in R_w} q_i^r \right) - \sum_{i \in I} \sum_{r \in R} v_i q_i^r
$$
where, $\mu_w$ and $v_i^r$ are Lagrange multipliers corresponding to the constraints. According to the Kuhn–Tucker conditions, the extreme point of the Lagrange function satisfies the following conditions [38]:

$$\frac{\partial L}{\partial q_i^r} = 0, \frac{\partial L}{\partial \mu_w} = 0, \frac{\partial L}{\partial v_i^r} = 0$$

(9)

Then, the equilibrium flow on route $r$ of travel mode $i$ can be finally obtained as follows:

$$q_i^r = Q_w \frac{\exp(-\theta c_i^r)}{\sum_{i \in I} \exp(-\theta c_i^r)}$$

(10)

The Equation (10) also proves that the traveler’s mode choice behavior follows the Logit model. The probability of the travel mode $i$ of route $r$ is:

$$P(i) = \frac{\exp(-\theta c_i^r)}{\sum_{i=1}^{n} \exp(-\theta c_i^r)}$$

(11)

Let us assume there are two travel modes to replace with public bikes, namely, walking (henceforth referred to simply as walk) and taxi. Suppose the walk speed $v_0$ is 4 km/h and the taxi speed $v_1$ is 50 km/h, the economy cost of the walk $c_0^r$ is 0, and the economy cost of the taxi $c_1^r$ is 11 Yuan since the maximum distance is within flag-fall price. The trip distance $d_r$ is from 0.4 km to 3 km with the increment of 0.2 km, $\gamma_1 = 0.9$, $\gamma_2 = 0.1$, $\theta = 1$. The cost of travel is then shown in Figure 1.

Figure 1. Relationship between the generalized travel cost and the trip distance.

As can be seen from the figure, the generalized travel cost of walk increases with distance, but that of taxi decreases with distance. When the trip distance is 1.4 km, the walk cost equals to the taxi cost. When the trip distance is longer than 1.4 km, walk cost is more than that of taxi.

The relationship between the probability of choosing walk or taxi is shown in Figure 2. As can be seen from the figure, when the trip distance is smaller than 1.4 km, the probability of walk is larger than that of taxi; and the larger the impedance perception coefficient $\theta$ is, the larger the probability of walk and the smaller the probability of taxi is. When the trip distance is larger than 1.4 km, the probability of taxi is larger than that of walk; and the larger the impedance perception coefficient $\theta$ is, the smaller the probability of walk and the larger the probability of taxi is.
3.2. Carbon Emission Calculation Model

The carbon emission refers to the emissions of CO₂ and other greenhouse gases. Six major greenhouse gases are highlighted in the Kyoto Protocol, CO₂, CH₄, NOₓ, N₂O, HFCs, and PFCs, of which CO₂ accounts for up to 60% of the carbon emission. The Intergovernmental Panel on Climate Change (IPCC) published a greenhouse gas accounting method which was based primarily on fuel combustion in 1996. We use the default emission factors and calculation model of major fossil fuels provided by the <2006 IPCC National Gas Guidelines> to calculate the carbon emission [39], which is:

\[
C = \sum_{r \in R} C_r
\]

where, \( C_r \) is the total vehicular travel distance of route \( r \), km; \( \beta \) is gasoline consumption per traveling distance, L/km—and according to national standards <Passenger car fuel consumption limit> (GB19578-2014) and GB279999-2014s, the average fuel consumption of passenger car in China is 0.0677 L/km; \( \rho \) is the density of gasoline, kg/L—and in the case of gasoline Nr. 92, the density is 0.725 kg/L; \( D_r \cdot \beta \cdot \rho \) is the quality of gasoline consumption; \( NCV \) is the average low calorific value of energy, GJ/t—and according to the <China Energy Statistical Yearbook 2006>, the \( NCV \) of gasoline is 20.908 GJ/t; \( CC \) is the carbon dioxide content of the fuel, tC/TJ—and according to the <Guide to Provincial Greenhouse Gas Inventory Preparation>, the CC of gasoline is 18.9; \( O \) is the oxidation rate, indicating the proportion of carbon in fossil energy converted to carbon dioxide, which is 96% according to <Greenhouse Gas Preparation Guidelines>; and finally, \( 44/12 \) is the conversion coefficient between carbon dioxide and carbon. The carbon emission calculation parameter values are shown in Table 1.

Table 1. The carbon emission calculation parameter values.

<table>
<thead>
<tr>
<th>The Type of Energy</th>
<th>Energy Low Thermal Value NCV (GJ/t)</th>
<th>Energy CO₂ Content CC (tC/TJ)</th>
<th>Oxidation Rate O</th>
<th>Emission Factor (t Carbon/t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>raw coal</td>
<td>20.908</td>
<td>25.8</td>
<td>96%</td>
<td>1.899</td>
</tr>
<tr>
<td>gasoline</td>
<td>43.070</td>
<td>18.9</td>
<td>96%</td>
<td>2.865</td>
</tr>
</tbody>
</table>

The other emissions, such as CO₂, CO, HC, NOₓ, PM2.5, etc., can be calculated from the automobile emission standards. All of the light-duty gasoline vehicles on sale and registered in China must meet the national emission standard VI(A) from 1 July 2020. The emission calculation model is:

\[
E_i = \sum_{r \in R} D_r \cdot \beta \cdot f_i
\]
where $E_i$ is the total emissions of different emissions; $D_r$ is the total vehicular travel distance of route $r$, km; $\beta$ is gasoline consumption per traveling distance, L/km; and $f_i$ is the emission factor of different emissions. The emission factors are shown in Table 2.

### Table 2. Vehicle emission factors.

<table>
<thead>
<tr>
<th>Vehicle Category</th>
<th>Test Quality</th>
<th>CO (mg/km)</th>
<th>THC (mg/km)</th>
<th>NMHC (mg/km)</th>
<th>NOx (mg/km)</th>
<th>N2O (mg/km)</th>
<th>PM (mg/km)</th>
<th>PN (mg/km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first class car</td>
<td>all</td>
<td>700</td>
<td>100</td>
<td>68</td>
<td>60</td>
<td>20</td>
<td>4.5</td>
<td>$6.0 \times 10^{11}$</td>
</tr>
<tr>
<td>The second class car</td>
<td>TM ≤ 1305</td>
<td>700</td>
<td>100</td>
<td>68</td>
<td>60</td>
<td>20</td>
<td>4.5</td>
<td>$6.0 \times 10^{11}$</td>
</tr>
<tr>
<td></td>
<td>1305 &lt; TM ≤ 1760</td>
<td>880</td>
<td>130</td>
<td>90</td>
<td>75</td>
<td>25</td>
<td>4.5</td>
<td>$6.0 \times 10^{11}$</td>
</tr>
<tr>
<td></td>
<td>1760 &lt; TM</td>
<td>1000</td>
<td>160</td>
<td>108</td>
<td>82</td>
<td>30</td>
<td>4.5</td>
<td>$6.0 \times 10^{11}$</td>
</tr>
</tbody>
</table>

### 4. Case Study

#### 4.1. Study Area

The research area is Ningbo city, which is an important port city in the southeast coastal region of China, and a sub-provincial city of Zhejiang Province. Ningbo covers a total area of 9816 km$^2$ with an urban area of 3730 km$^2$, and its permanent population is 8.542 million, while its GDP was CNY 1.24 trillion in 2020. Ningbo has 2 counties, and 2 county-level cities, and 6 districts, among which Haishu District, Jiangbei District, Beilun District, Zhenhai District, and Yinzhou District are the central ones. As of August 2018, there were 35,800 public bikes in Ningbo. The heat map of the citywide bike stations with 800 m as a spatial unit was created in ArcGIS, as shown in Figure 3. As can be seen from the figure, the density is at its highest in the center area of each district. The bike stations are more concentrated in the city center, where there are two or more stations per spatial unit.

![Figure 3. The heat map of bike stations.](image)

#### 4.2. Data Preprocessing

The data set we analyzed contains the complete record of all activities of public bikes in Ningbo from 1 July 2018 to 31 July 2018, including 1281 bike stations, 31,623 bikes, 44,623 users, and 2,337,721 rental data. The data set is provided by the Ningbo Public Bike Service Development Co., Ltd., Ningbo, China. Each piece of raw data includes 9 elements, which are the user’s-card number, vehicle number, rental time, rental station number, rental station name, return time, return station number, return station name, and times of rental and return.
First, we utilized the bike function in the Ningbo citizen card app to locate each bike station and obtained the number of parking docks at each station. Secondly, we used the coordinate picking function of the Baidu map open platform to manually pick up latitude and longitude coordinate data of all stations. Thirdly, we matched the coordinate’s data and the parking dock numbers to each bike-hiring travel data by Python. Then, we got a data set with the latitude and longitude coordinates of the stations.

The distance and speed of each trip still needed to be estimated. First, we imported the Ningbo city road network in ArcGIS, which includes provincial roads, county roads, urban roads, pedestrian roads, and other road data. Secondly, the Analyst feature obtains data on the shortest travel distance for each trip, which we use as the user’s travel route distance. Because the route is the shortest one between the rental station and the return station, the distance of the actual travel distance is underestimated. After testing, the user spends 30 s to pick up or park the bike. By subtracting the pick and park time from the rental time, the estimate of the travel time was acquired. The travel speed was estimated by the travel route distance and the estimated travel time. Finally, we attain the full data set including the latitude and longitude coordinates of the origin and destination points, the number of parking docks, route distance, travel speed, etc. Each data point now contains 17 elements or pieces of information.

The following conditions were set as anomalous data and excluded from the dataset: (1) the rent and return time is more than 1 h; (2) the rent and return time is less than or equal to 1 min; (3) the travel route distance is less than 100 m; (4) the travel route distance is more than 10 km; (5) the average travel speed is more than 30 km/h; (6) the average travel speed is below 1 km/h. After the data cleansing, a total of 546,897 travel data were deleted and 1,783,824 valid travel data were left. The data cleaning process explained above is shown in Figure 4.

![Figure 4. Data cleaning process.](image)

4.3. Characteristics of Bike Trips

In a month, the total travel distance of all bikes is 3,109,605.90 km, with an average trip distance of 1.74 km and a standard deviation of 1.26 km. The total travel time of all bikes is 380,821.08 h, which is equivalent to 43.47 years, with an average trip time of 12.81 min and a standard deviation of 9.81 min. The average travel speed for all trips is 9.29 km/h and the standard deviation is 3.66 km/h. The bike usage rate is 1.82 trips per day per bike in July.
4.3.1. Temporal Distribution of Trips

The distribution of daily trip numbers from Monday to Sunday by hours is shown in Figure 5. As can be seen from the figure, an evident bimodal structure of bike usage is presented. The number of trips in morning and evening peak hours is significantly higher than that at other times, which is consistent with daily commuting. Thus, this indicates that many users take public bikes as a daily commuting tool. The trip distribution structure of workdays is similar, and the structure of Saturday and Sunday is similar, while the bimodal structure is more obvious on workdays than at weekends. The morning peak of trips on workdays is at 7 am and the evening peak is at 5 pm. At weekends, the morning peak occurs at 8 am, and the evening peak occurs at 5 PM (Saturday) and 6 PM (Sunday), which shows that the weekend peak hour is about an hour later than that on workdays. The average number of trips during morning peak hour is 19,700 on workdays and 11,200 at weekends, i.e., 1.76 times higher for workdays than for weekends. The average number of trips in the evening peak hour is 17,700 on workdays and 9000 at weekends, i.e., 1.97 times greater for workdays than weekends. All this further illustrates the role of public bikes as a tool for daily commuting. In addition, the peak time on Sunday afternoon is longer, from 16:00 to 20:00. Finally, the trip distribution structure of Monday and Tuesday is more similar than that of Wednesday to Friday, and the number of trips of Monday and Tuesday is greater.

Figure 5. The time distribution of the number of trips.

4.3.2. Distribution of Travel Distance

The daily travel distance and time between origin stations and destination stations is shown in Figures 6 and 7. It can be seen that the travel distance is in the range of 0.1 km to 10 km, these being the set boundary values of data cleaning. The average travel distance is 1.74 km, and the median distance is 1.44 km. In addition, the travel time of trips is in the range of 1 min to 60 min, which are also the boundary values of data cleaning. The average travel time is 13.4 min, and the median is 10.1 min. We can therefore conclude that the trips are short-distance trips, which indicates that public bikes are the preferred choice of “the last kilometer”.

![Figure 5. The time distribution of the number of trips.](image-url)
Figure 6. Daily distribution of travel distance.

Figure 7. Daily distribution of travel time.

Figure 8 shows the frequency distribution of all trip distances. It can be seen that the most frequent of travel distances is about 0.7 km, followed by 1 km and 0.4 km. The number of trips for which travel distance is less than 1.6 km accounts for 70% of all trips, which indicates that public bikes mainly satisfy the short-distance trip. People may consider riding when the trip distance is longer than 400 m. Since there is no actual route data, the shortest route between the origin and destination points is used to replace the actual trip route. The number of trips for which travel distance is longer than 3.4 km accounts for only 10% of all trips. As the trip distance increases, the frequency of trips decreases.

Figure 8. Frequency distribution of travel distance.
4.3.3. Characteristics of the Turnover Rate of Parking Docks

The turnover rate of parking docks is the ratio of the total number of rent and return bikes per unit of time to the number of parking docks. The rent turnover rate of parking docks is the ratio of the number of rental bikes per unit of time to the number of docks. The return turnover rate of parking docks is the ratio of number of return bikes per unit of time to the number of parking docks. As shown in Figures 9 and 10, there are 1281 stations in the city, and the average total turnover rate is 0.17 times/hour. The total turnover rate range is [0, 11.97], rent turnover rate is [0, 6.31], and return turnover rate is [0, 5.66]. The hourly turnover rate is the same as the number of trips per hour, showing an evident bimodal structure, and the hourly turnover rate is low during both peak and flat hours. This indicates that the utilization rate of parking docks is low.

Figure 9. Turnover rate of each station.

Figure 10. Hourly mean turnover distribution.

Figure 11 shows the hourly turnover frequency distribution of all sites, where it can be seen that the turnover rates of 0.05–0.2 times/hour/dock account for more than 80% of cases, while those over 0.5 times/hour/dock account for less than 5%. Even in peak hours, the frequency distribution of low turnover rate is high, while that of high turnover rate is low. The rental turnover rate in the evening peak is more concentrated than that in the early peak.
4.4. Carbon Emission Reductions Analysis

We assume that there are two alternatives for riding bikes, which are walk and taxi. If people choose to walk on foot, there is no carbon emissions or environmental pollution, whereas if people choose to take a taxi, there will be carbon emissions and environmental pollution. Therefore, environmental benefits of riding bikes are ascribable to replacing travel by taxi.

In the 1980s, the new urbanism method of creating and revitalizing urban communities appeared in the United States, and emphasized that the formation of residential communities could be measured by walking distance [40]. The size of the community would not exceed a radius of about 400 m or about 5-min walking distance. Employing this idea, the distance of 400 m is used as the minimum threshold for walking ($d_{\text{min}}$), and 3 km as the maximum threshold for walking ($d_{\text{max}}$). If the trip distance is less than or equal to $d_{\text{min}}$, then the probability of people choosing to walk is 1; if the distance exceeds the maximum threshold, then the probability of people choosing to walk is 0; if the trip distance is between the minimum threshold and maximum threshold, then the probability of people choosing to walk decreases with the trip cost, calculated by the probability model.

The carbon and other emissions reduced by public bikes in Ningbo City based on public bike travel data is calculated by Equations (10) to (14). First, we use the proposed probability model of travel mode which is elaborated in Section 3.1 to calculate the travel volume of two alternative travel modes, specifically Equation (11). Secondly, we use the emissions calculation model in Section 3.2 to calculate carbon emissions and other emissions of all taxi trips, given by Equations (13) and (14). From the calculations, the public bikes in Ningbo City saved 1704.42 tons of gasoline consumption, and reduced carbon emissions by 4883.79 tons, as well as carbon dioxide emissions by 1638.91 tons and nitrogen oxide emissions by 3.47 tons in 2018. According to the data of population, area, and economic indicators of Ningbo in the Ningbo volume of “China Statistical Yearbook (County-Level) 2018” [41], the district-wide emissions reduced by public bikes is shown in Table 3. As can be seen, the largest environmental gain from the public bikes is Jiangbei District, where the average reduction of carbon and of carbon dioxide emissions were of 2.49 tons/km² and 0.84 tons/km², respectively. According to the population base, the public bike reduction in carbon emission per capita is 1.97 kg/person, and the biggest benefit is in the Yinzhou District, where the carbon emission per capita is 2.07 kg, and CO$_2$ emission per capita is 0.66 kg. It can be seen that the energy conservation and emissions saved by the public bikes are considerable.
Table 3. Public Bike Environmental Benefits Index for Ningbo City.

<table>
<thead>
<tr>
<th>District</th>
<th>Area (km²)</th>
<th>Population (People)</th>
<th>Fuel Consumption (t)</th>
<th>Carbon Emissions (t)</th>
<th>CO₂ (t)</th>
<th>NOₓ (t)</th>
<th>CO₂ per Square Kilometer (t/km²)</th>
<th>C Emissions per Capita (kg/Person)</th>
<th>CO₂ per Capita (kg/Person)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haishu</td>
<td>595</td>
<td>629,970</td>
<td>415.04</td>
<td>1189.23</td>
<td>399.08</td>
<td>0.85</td>
<td>2.00</td>
<td>1.89</td>
<td>0.63</td>
</tr>
<tr>
<td>Jiangbei</td>
<td>208</td>
<td>257,730</td>
<td>180.83</td>
<td>516.15</td>
<td>173.88</td>
<td>0.37</td>
<td>2.49</td>
<td>2.01</td>
<td>0.67</td>
</tr>
<tr>
<td>Zhenhai</td>
<td>246</td>
<td>260,828</td>
<td>178.09</td>
<td>510.30</td>
<td>171.25</td>
<td>0.36</td>
<td>2.07</td>
<td>1.96</td>
<td>0.66</td>
</tr>
<tr>
<td>Beilun</td>
<td>599</td>
<td>423,717</td>
<td>279.34</td>
<td>800.41</td>
<td>268.60</td>
<td>0.57</td>
<td>1.34</td>
<td>1.89</td>
<td>0.63</td>
</tr>
<tr>
<td>Yinzhou</td>
<td>814</td>
<td>902,151</td>
<td>631.12</td>
<td>1865.70</td>
<td>626.10</td>
<td>1.33</td>
<td>2.29</td>
<td>2.07</td>
<td>0.69</td>
</tr>
<tr>
<td>Ningbo</td>
<td>2462</td>
<td>2,474,396</td>
<td>1704.42</td>
<td>4883.79</td>
<td>1638.91</td>
<td>3.47</td>
<td>1.98</td>
<td>1.97</td>
<td>0.66</td>
</tr>
</tbody>
</table>

The relationship between the carbon emissions, fuel consumptions and population size are shown in Figure 12. As can be seen, the carbon emissions and fuel consumptions are positively related to the population size. The greater the population, the more public bikes are used, and the greater the reduction in fuel consumption and emissions.

The carbon emissions are positively linearly related to the average hourly total turnover rate and the average rental turnover rate of all stations in the road network. The relationship between the carbon emissions and the average total turnover rate is \( y = 127.31x - 5.98 \), and its correlation coefficient is \( R^2 = 0.965 \)—where \( y \) is the total carbon emissions, tons; and \( x \) is the average hourly total turnover rate, times/hour/dock. The relationship between the carbon emissions and the average rental turnover rate \( (x_r) \) is \( y = 254.07x_r - 5.93 \), and its correlation coefficient \( R^2 = 0.975 \). It can be seen that the average rental turnover rate is a perfect index to reflect the carbon emissions of the road network.

Figure 13 shows the spatial distribution of the carbon emission reduction and fuel consumption in districts of Ningbo City. As can be seen from the figure, the Yinzhou district has the highest fuel consumption and carbon emission savings, followed by Haishu District, Beilun District, Jiangbei District and Zhenhai District. This is because the area of Yinzhou District is the largest, and has the most scenic spots and commercial areas and most developed transportation hub in the district; thus, the environmental gain effect is the most obvious.
Figure 13. Carbon emission and fuel consumption in districts.

5. Conclusions

With the development of technology and changes of lifestyle, the shared travel mode, such as bikes, electric bikes, vehicles etc., becomes an effective way to reduce energy consumption and emissions. This paper studies the potential for carbon emission reduction from public bikes. We use the approach of estimating the capability of shared bikes to reduce carbon emissions by substituting them for private car travel. Two models are built to estimate their capability. The first model is the travel mode choice model, which is based on the Logit-based stochastic user equilibrium model to minimize the travel cost. The second model is the emission calculation model based on the IPCC greenhouse gas accounting method and automobile emission standards.

We use the travel data of public bikes in Ningbo as our case study, which contains more than 233 million trips. First, the travel characteristics of public bikes was analyzed. It is found that the average travel distance is 1.74 km, the median distance is 1.44 km, and the most frequent travel distance is only 0.7 km. The average travel time is 12.81 min, and the average travel speed is 9.29 km/h. The bike journeys are mainly in the rush hours of workdays, which means the bikes are mainly used for commuting. According to the characteristics of the travel distance and the time of trip generation, we conclude that shared bikes are an important aspect of combined travel. Therefore, the bike sharing system has great potential to affect people’s travel modes, particularly promoting transits onto public transport. Shared bikes supply more opportunities to use public transit facilities when the density of the public facility network is imperfect. Moreover, according to the data analysis, we found the turnover rate of parking docks is low, being less than 0.2 times/hour at over 80% of docks. Therefore, there is much room for improvement in the performance of public bikes. Based on the trip data, we estimate the capability for carbon emission reductions of public bikes to be 1.97 kg/person. It is positively linearly related to the average hourly total turnover rate, which means the turnover rate is a great parameter to reflect carbon emission reduction capability. As previously analyzed in terms of travel characteristics, public bikes are one tool for promoting combined travel. Therefore, carbon emission reductions caused indirectly by traveling on public bikes would be considerably greater if the incremental increase in public transit caused by use of public bikes is taken into account. The carbon emission reduction potential from the changes of transport structure is significant.

According to the analysis in our case study, decision-makers need to apply more efforts to improve the utilization rate of public bikes, e.g., improve the efficiency of the public bike site layout, supply more measures to encourage travel by public bike, etc. Considering the path dependencies in regions with a high percentage of fossil fuels, it is not possible to change the energy mix in the short term; therefore, this study suggests the government should adopt environment-friendly regulatory policies, for instance, subsidizing stakeholders to encourage the adoption of green practices for transport, stimulating citizens
to travel by public transit or other green modes of travel through economic or spiritual rewards, etc. The government should innovate the incentive mechanism, rather than using a charge incentive only. Taking the public bikes of Ningbo as an example, in order to encourage citizens to use public bikes, they are totally free of charge, yet the utilization rate is quite low.

In the development of urban transport, transport modes become more diverse and open, with an optimistic view that the era of the private car is about to end, and that urban interest in cycling is growing. Yet, the existing transport system has been designed for the private car, and the balance between private car and public transport modes deserves further focus and efforts. Policies for optimizing the transport structure as well as for adaptation of clean and sustainable fuels will help to reduce carbon emissions.

The potential environmental benefits resulting from a change of transportation structure and of vehicles types would be considerable; such changes could include, for instance, a combination of public transit with shared modes of travel, as well as a vehicle fleet composed of a mix of vehicle types—internal combustion engine vehicle (ICEV), plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV), etc. The environmental benefits from shared bikes derive not only from direct bike travel, but also from the combined traveling styles made attractive by bikes. More detailed studies on the capability of combined travel modes including shared bikes to induce carbon reduction will be published in a later paper.

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