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A Cycling Friendliness Measurement System for Dockless Bike-sharing Dynamic Scheme

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Abstract. *The rapid growth of Dockless Bike-sharing (DLBS) provides an excellent opportunity to meet the strong demand for convenient green travel services. However, with the increasing number of cyclists and DLBS, the issue of DLBS friendliness faces several challenges: (1) the hardness of renting in empty fences; (2) the difficulty of parking in overload fences; (3) different road conditions have different effects on cycling friendliness. To deal with these challenges, we design a DLBS friendliness (DLBSF) system, consisting of DLBS recommendation (DLBSR) system and DLBS scoring (DLBSS) system to comprehensively alleviate the problem of decreasing friendliness. The former optimizes cycling friendliness by first identifying the overload fences where the morning peak tide phenomenon is most prominent, and then provides guidance for cyclists to park the nearest idle fences. The latter gives the riding friendliness scheme by scoring and analyzing each road section to improve friendliness. Experiments on real-world DLBS datasets verify the accuracy, effectiveness, and feasibility of the proposed DLBSF system.*
Keywords: Dockless Bicycle-sharing system, cycling friendliness, HNSW algorithm, user-based guidance

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1. **Introduction.** In recent years, with the improvement of urban traffic construction and public transport facilities, the intelligent transportation system has also entered a stage of rapid development [1, 2, 3]. However, the first/last mile problem is the most immediate problem for the public in smart cities [4, 5, 6]. The emergence of DLBS solves this problem, but it brings traffic congestion and tidal phenomenon (In the morning and evening peak hours "no bicycles renting and parking" phenomenon). On the other hand, due to complex factors such as the surge of urban population and the complex road environment, the cycling friendliness of existing urban different roads are quite different, which also puts forward higher requirements for urban management [7, 8].

Many factors affect road conditions. For example, traffic congestion due to road construction, In the morning and evening rush hour, mixed motor vehicles and bicycles on the road, some roads with poor night lighting conditions, etc. Due to the complexity of the factors leading to the decline of cycling friendliness, this work mainly analyzes and solves the problem of cycling friendliness from the origin (O) and destination (D) of cycling, and the cycling process. Multi-source datasets are collected in this work, such as the urban road network, the flow of people and DLBS on the subway station, weather data, etc.

In the literature, numerous methods have been proposed for DLBS scheduling [9, 10, 11]. These methods can be classified as static bicycle scheduling systems and dynamic bicycle scheduling systems. However, they usually lack the user perspective to analyze and solve cycling friendliness and just redistribute the bicycles. Moreover, they did not consider the effects of weather and road conditions on cycling friendliness. Furthermore, the origin and destination of cycling, and the cycling process are closely related to cycling friendliness. Few papers comprehensively analyze cycling friendliness from three aspects. Tidal zones are not divided, but the study of these tidal zones is important for analyzing and solving friendliness problems.

In this work, we propose a DLBSF system to analyze and solve the problem of cycling friendliness from two aspects. For the friendliness of the origin and destination of cycling, a DLBS recommendation (DLBSR) system is constructed to identify the most prominent zones of the morning peak tide phenomenon by HDBSCAN-based algorithm, and then guide the cyclists to park adjacent idle fences for alleviating the tide phenomenon of overload fences, to optimize the cycling friendliness. For the cycling process, a DLBS scoring (DLBSS) system is constructed to analyze the road sections and provide a cycling friendliness scheme to improve the friendliness of the cyclists.

The main contributions of this work are summarized as follows:

• We propose a DLBSF system to analyze and solve cycling friendliness through the origin and destination of cycling, and the riding process, which can also provide a reasonable recommendation.

• The tidal zones are identified by the HDBSCAN-based clustering algorithm, and then guide the cyclists to park adjacent idle fences to optimize cycling friendliness.

• Extensive experiments on real-world DLBS datasets verify the accuracy, effectiveness, and feasibility of the proposed DLBSF system.

The rest of the paper is organized as follows: In Section 2, we summarize the related work on bike-sharing planning in recent years, definition and notation are provided in Section 3. Then, we introduce the methodology framework and the detailed two systems in Section 4, and we conduct abound experiments and analyze the experimental results in Section 5. Finally, we conclude this work in Section 6.

2. **Related work.** Abound efforts have been made in researching data mining techniques and big data to build smart cities [1, 11]. Numerous studies of smart cities and DLBS networks attract both fields of academia and industry [12, 13, 14]. Focusing on the analysis and planning of bike-sharing demands, Zhang et al. used CNNs to learn the spatio-temporal correlation characteristics jointly from low-level to high-level layers for bike-sharing trips [15]. Etienne et al. analyzed the use of DLBS networks by using model-based to count series clustering [16]. Cazabet et al. researched cycling rules from the perspective of data analysis and signal processing [17], in which a cycling periodic model was built by analyzing the features of space, time, and cyclists. However, most existing systems are built to predict the bike-sharing demands, they pay little attention to research on cycling friendliness.

There are massive approaches focused on location prediction [18, 19, 20] in spatio-temporal travel data. Jia et al. [20] proposed a spatio-temporal Bayesian model to predict bike-sharing location based on his influential adjacent locations. Ying et al. [21] further proposed a GTS-based location prediction method and introduced a Geographic-Temporal-Semantic (GTS) model, which collected the trajectories of cyclists and calculated the similarity of the trajectories and movement between cyclists. Graph Neural Network (GNN) is a valid deep learning model used in bike-sharing demand prediction [22, 23]. Lin et al. used the GNN method to predict the hour-level demands of bike-sharing stations in the DLBS network. They used the Long Short-Term Memory (LSTM) to capture the temporal dependency of bike-sharing demand sequences [24]. Gast et al. [25] introduced a generalized regression neural network to predict bike-sharing demands.

Focusing on the layout of bike-sharing stations, numerous schemes were carried out [26, 27]. Ma et al. proposed a hierarchical bike-sharing dispatching strategy for dynamic bike-sharing demand [28]. Deng et al. [29] discussed the layout optimization of bike-sharing stations by the AHP-based method. Jiang et al. [30] further analyzed the GPS trajectory of bike-sharing and detected K-primary corridors on the road network. However, most of the existing researches focus on the traditional station/dock-based bike-sharing (SDBS) network, and they design the static bike-sharing station layout at the initial phase. Owing to the high operating costs, once these stations are built, the location of these stations will not change. Different from the existing researches, we focus on the dynamic layout of the electric fences for the DLBS network, and update the electric fences between different time periods according to the actual bike-sharing demands.

However, there is little literature on the identification of bike-sharing tide zones. Policy guidance on the electric fence parking and planning management scheme remains unclear in response to the demands of various stakeholders. Existing researches pay little attention to research on cycling friendliness.

Therefore, in this work, we propose a novel DLBSF system, consisting of a DLBS recommendation (DLBSR) system and a DLBS scoring (DLBSS) system to comprehensively alleviate the problem of decreasing friendliness. For DLBSR, measures and solves the cycling friendliness through the origin and destination of cycling. For DLBSS, gives the cycling friendliness scheme by scoring and analyzing each road section to improve friendliness.

3. Preliminaries.

In this section, we first introduce the definitions and notations.

3.1. Definitions and Notations.

For ease of illustration, we first summarize the definitions and notations.

Definition 1: Tidal zones. The tidal zones are defined as the zones where bike-sharing cannot be rented or parked in some zones during morning and evening rush hours.

Definition 2: Cycling friendliness. The friendliness of the origin and destination of cycling is the convenience of renting and parking the bike-sharing; the friendliness of the cycling process is the convenience of different roads during the cycling process.

Definition 3: Bicycle utilization rate. The proportion of cycling time per unit time.

Table 1. List of notations

Symbols	Description
T	Bike-sharing data acquisition time step.
Q	Road segment subset.
N	Bike-sharing data subset.
M	Electric fence subset.
K	Main road segment subset.

Table 2. List of Indicators

Indicators	Description
P_m	The remaining number of bikes in the *m-th* fence.
D_m	The bike-sharing density of the *m-th* fence.
A_m	The Number of active days in the *m-th* fence.
L_m	The length of guidance of the *m-th* fence.
G_m	The evaluation score of the *m-th* fence.
F_m	The cycling friendliness of the main road section k.

4. Methodologies.

4.1. Methodology Framework.

The methodology framework of this work is shown in Figure 1. Multisource data including electric fence data, DLBS trip data, and DLBS order data is collected in this work to support the guidance system and cycling friendliness scheme. The methodology framework is as follows.

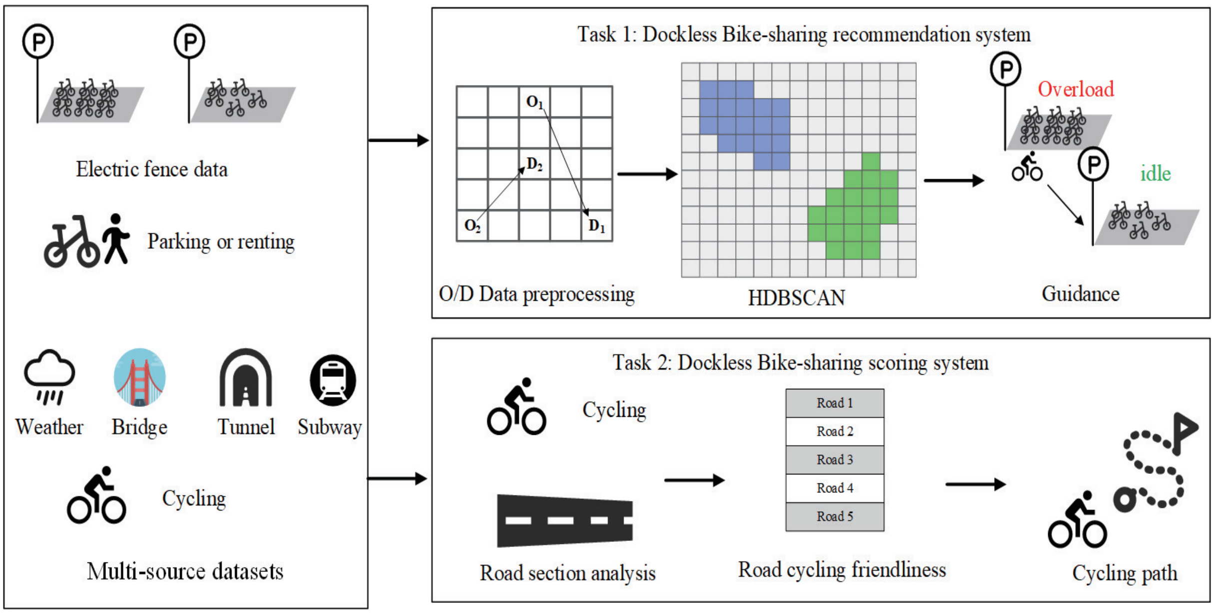


FIGURE 1. Methodology framework.

Task 1: Dockless Bike-sharing recommendation system. The origin and destination of each trip are extracted from DLBS trip data. The longitude and latitude of each fence center with the number of bike-sharing are packed as the input of HDBSCAN. Then, the tidal zones are identified. Finally, providing the optimal bicycle guidance for the DLBS network.

Task 2: Dockless Bike-sharing scoring system. The road network of Xiamen data is used to match the road bike-sharing information by Hierarchical Navigable Small World (HNSW) algorithm. Then, we analyze the bicycle utilization rate of different road sections. Finally, the friendliness score is evaluated to provide a cycling friendliness recommendation.

4.2. **Dockless Bike-sharing recommendation system.**

4.2.1. *Identification of the tidal zones.* The tidal zone is defined here as a zone where numerous shared bicycles flow in or out in a short time. The different travel behaviors of cyclists lead to different functions of parking attributes at each fence, resulting in tidal zones. In terms of time characteristics, the demand for each tidal zone is time-varying, and each period has different needs. In terms of spatial characteristics, we found that each electric fence is connected to the other, forming a continuous single zone. Therefore, according to the spatial-temporal characteristics of the tidal zone, the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) clustering algorithm is used to identify the tidal zone.

The longitude and latitude of each fence center with the number of bike-sharing are packed as the input of HDBSCAN. The procedure of tidal zones clustering in out work is as follows:

First, we establish a minimum spanning tree, with the mutual reachable distance between electric fences as the edge, and transform the tree into a hierarchical structure. Next, we use the input parameter min_cluster_size to find the compressed cluster tree. Finally, the densityadaptive clustering result is obtained by a stability function.

Let α_i and β_i be the latitude and longitude of the fence v_i, we can use the Haversine method to calculate the distance between fences $v_i(\alpha_i, \beta_i)$ and $v_j(\alpha_j, \beta_j)$:

$$d_{ij} = 2R \cdot \sin\sqrt{H(\frac{d}{R})} = 2R \cdot \sin\sqrt{(H(|\beta_i - \beta_j|) + \cos(\beta_i)\cos(\beta_j)H(|\alpha_i - \alpha_j|)} \tag{1}$$

where R is the radius of the earth, usually set to 6371.0 km, and the Haversine function $H(\theta)$ is defined as:

$$H(\theta) = \sin^2(\frac{\theta}{2}) = \frac{1}{2}(1 - \cos(\theta)). \tag{2}$$

4.2.2. *Evaluation of the tidal zones and Guidance.* In the above sections, the tidal zones could be identified with high precision. In this section, we provide the guidance program from three aspects (the flow of each fence, the density of each fence, and the active days of the fence). The following paragraphs explain why certain aspects are chosen.

For bike-sharing flow, it represents the level of demand and state in a zone. In general, it contains positive and negative flow, (i.e., positive flow represents $P_m > 0$, negative flow represents $P_m < 0$). The former represents that supply exceeds demand, while the latter means that supply is less than demand.

For the fence demand density, demand density is defined here as the ratio between the fence parking demand and the fence area. The spatial-temporal variation of density leads to the different congestion states of the fence. For example, the area of the tidal zone with the same flow will be very different, the high flow zone is not necessarily dense, which results in errors.

For the active level, it describes the active days of $P_m > 0$ for the different zones. The different active levels mean the degree of demand exceeds supply. For example, after all the existing number of bicycles in different fences flow out, the staff manually dispatched bicycles from other fences.

According to Equations (3), (4), and (5), the flow of each fence, the density of each fence, and the active days of the fence are calculated respectively.

The parking bike-sharing flow P_m of *m-th* fence at time t can be calculated as follows:

$$P_m = N + BF_{in} - BF_{out} \tag{3}$$

where P_m denotes the remaining number of bicycles in *m-th* fence, BF_{in}, BF_{out} represent bike-sharing trips arriving in electric fences and trips departing from electric fences, and N is the number of existing bicycles in electric fences.

The fence demand density D_m can be calculated as follows:

$$S_m = length_m \cdot width_m \tag{4}$$

$$D_m = \frac{P_m}{S_m} \tag{5}$$

where $length_m$ and $width_m$ represent the length and width of the fence, respectively, S_m is the area of the *m-th* fence, D_m is the bicycle density of the fence.

The active level of the fence A_m can be calculated as follows:

$$A_m = \sum_{t-1}^{T} a_m \begin{cases} 1 & if\, P_m > 0 \\ 0 & otherwise \end{cases} \tag{6}$$

where T is the total sampling days. a_m represents the active days for the fence.

To more accurately identify the overload fence, we sum up the Z-score normalized the fence demand density and the parking bike-sharing flow to get the overload fences. The comprehensive index O_m can be calculated as follows:

$$zscore(\cdot) = \frac{x-\mu}{\sigma}; \tag{7}$$

$$O_m = zscore(D_m) + zscore(P_m), \tag{8}$$

where $zscore(\cdot)$ is the standardized equation. o_m is the comprehensive index for the *m-th* fence.

Finally, cyclists set their acceptable range, generally about 200 - 500 meters. DLBSR system sums up standardized the comprehensive index, the guidance distance, and the activity level of the fence to obtain the recommended index, as shown in Equation (9).

$$G_m = w_o \cdot zscore(O_m) + w_l \cdot (L_m) + w_a \cdot zscore(A_m), \tag{9}$$

where $zscore(\cdot)$ is the standardized equation. G_m is the recommended index for the *m-th* fence, L_m is guidance distance. w_o, w_l, w_a are the comprehensive index weight of the overload fence, the guidance distance, and the activity level of fence weight, respectively.

It should be noted that after the cyclist accepts the guidance decision, the number of bike-sharing in the target fences needs to be temporary + 1, which prevents the problem of all bicycles rushing to the same fence due to simultaneous multi-bicycle scheduling at close times. It prevents local optimums and new tidal zones from occurring, achieving the global balance.

4.3. **Dockless Bike-sharing scoring system.**

4.3.1. *Riding route matching.* The road network of Xiamen data is used to match the road bike-sharing information by the HNSW algorithm. HNSW is improved from Navigable Small World (NSW). The composition of NSW is to find the nearest points by randomly initializing the sample points when adding new sample points to the graph, and connecting the new points with the nearest points. HNSW expands the algorithm of multi-layer NSW. Its search algorithm is an iterative greedy algorithm starting from the highest level. It starts from a point in the current layer, initializes the top-level starting point, and the starting point in other layers depends on the search results of the previous layer. The current optimal result is calculated in each layer until the bottom layer, and the bottom layer search result is returned as the nearest neighbor of the initial query point. The algorithm is shown in Figure 2. The details are described as follows.

Input: training data set:$Z = (x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)$, where $x_i \in X \subseteq R^N$ is the feature vector of the sample set,$y_i \in Y \subseteq R^N$ is the category of the sample, $i = 1, 2, \ldots, N$

Output: the category y_i of the sample x_i and the distance between samples.

Finding the nearest J points to the sample x in the training set Z according to the selected distance formula. The category is determined by the nearest distance rule in the neighborhood.

$$y = argmax_{c_j} \textstyle\sum_{x_i \in N_j(x)} I_{(y_i - c_j)}, j = 1, 2, \ldots, J \tag{10}$$

where I is the indicator function, i.e., $I = 1$, if $(y_i = c_j)$, else $I = 1$.

The distance is calculated by Equation (1).

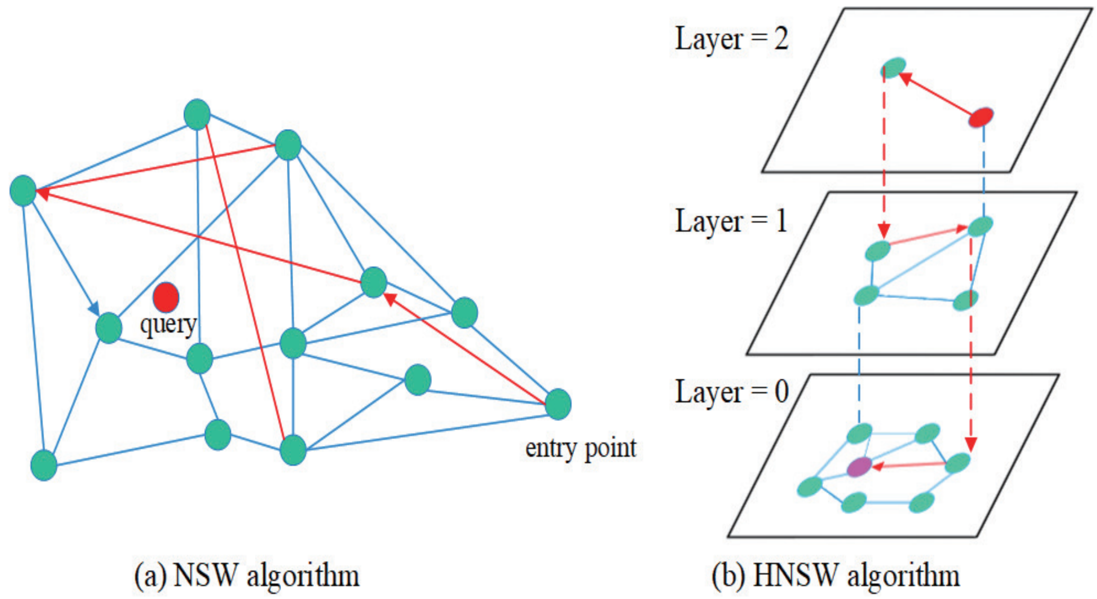


FIGURE 2. NSW and HNSW algorithm.

4.3.2. *Dense cycling route identification and cycling recommendation.* After the above cycling route matching, the friendliness score is evaluated for the bike-sharing data matching each road, which is calculated by Equation (10):

$$R_k = \sum_{q=1}^{Q} r_q (k = 1, 2, 3, \ldots, K); \tag{11}$$

$$U_k = \frac{\sum_{q=1}^{Q} u_q}{Q} (k = 1, 2, 3, \ldots, K); \tag{12}$$

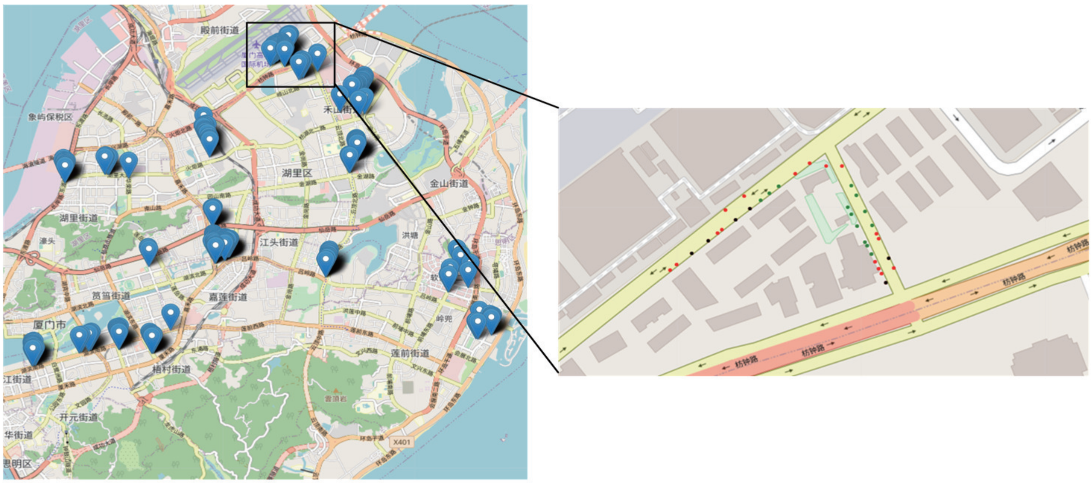
$$F_k = \frac{S_k}{U_k + \boldsymbol{\varepsilon}} (k = 1, 2, 3, \ldots, K); \tag{13}$$

$$F_k^* = \frac{F_k - F_k^{min}}{F_k^{max} - F_k^{min}} \tag{14}$$

where R_k represents the total distance of road section k, U_k represents Unit Riding Time for Section k, i.e., the proportion of cycling time per unit time on section k, F_k represents cycling friendliness on route k. In addition, to avoid $U_k = 0$, $\boldsymbol{\varepsilon}$ is a minimal value close to zero, F_k^* is the normalization of cycling friendliness.

The cycling friendliness of each road is calculated by Equation (14) and sorted in descending order. Finally, the DLBS scoring system model recommends high-rated roads for cyclists. Cyclists can choose their path according to the cycling friendliness of each road to improve the cycling experience.

5. **Experiments.** In this section, we conducted experiments on real-world datasets to verify the feasibility of the proposed DLBSF system. We collected bike-sharing order datasets, electric fence datasets, and cycling trajectory records in Xiamen city from December 21 to 25, 2020. (Monday to Friday). There are 12 million trajectory data (recorded once in 15 seconds), 14071 fences, and 600,000 orders.



(a) Distribution of the top 40 tide zones (b) Fences distribution in a tidal zone

FIGURE 3. The tidal zones distribution and a tidal zone containing 35 electric fences.

5.1. **Datasets.** Cycling trajectory records are collected from the cycling behaviors. Each cycling trajectory data contains the bike ID, source of bike, longitude, latitude, and the timestamp of collection. Electric fence datasets are collected from Streets in Xiamen. Each electric fence data contains the fence ID and electric fence position coordinates. Bike-sharing order datasets are routinely collected from all stationary bikes. Each order data contains the bike ID, longitude, latitude, the locking status of bikes, and the updated timestamp of the locking status. Due to the inaccurate coordinate positioning of some shared bicycles, they are located outside Xiamen City. We preprocessed the data, after data cleaning and filtering, obtained valid datasets.

5.2. **Case study.**

5.2.1. *Research on the Origin and Destination of Cycling.* The clustering results analysis and scheduling feasibility under the comprehensive index O_m are discussed. Figure 3 shows the tidal zones distribution and a tidal zone containing 35 electric fences.Figure 3(a) shows the tidal distribution according to the comprehensive index O_m, the top 40 tidal zones contain 353 fences, and show the tidal phenomenon. It is found that these tidal zones are CBDs, commercial zones, and schools, which are in line with the actual situation. The overload fences are obtained by the comprehensive index O_m, and the minimum congestion degree in the overload fences is 1.616992.

A tidal zone is selected for observation to prove whether there is a large tidal gap between adjacent electric fences, as shown in Figure 3(b). The electric fences in the adjacent fence with $O_m > 8$, which are marked as black, the remaining electric fences with $1.61 < O_m < 8$ are marked as red, and the idle fences are marked as green. It is found that there is also a great gap in the same tidal zone, which fully shows that there are also some relatively idle fences in the tidal zone for bike-sharing guidance, which provides feasible support for the guidance schemes.

Figure 4 shows details of the 353 fences in the top 40 tidal zones. It is found that 52.4% of the 353 fences are not overload fences, while the remaining 47.6% of the overload fences contain 92.9% (14,766) of the bikes. It also provides feasible support for the guidance schemes.

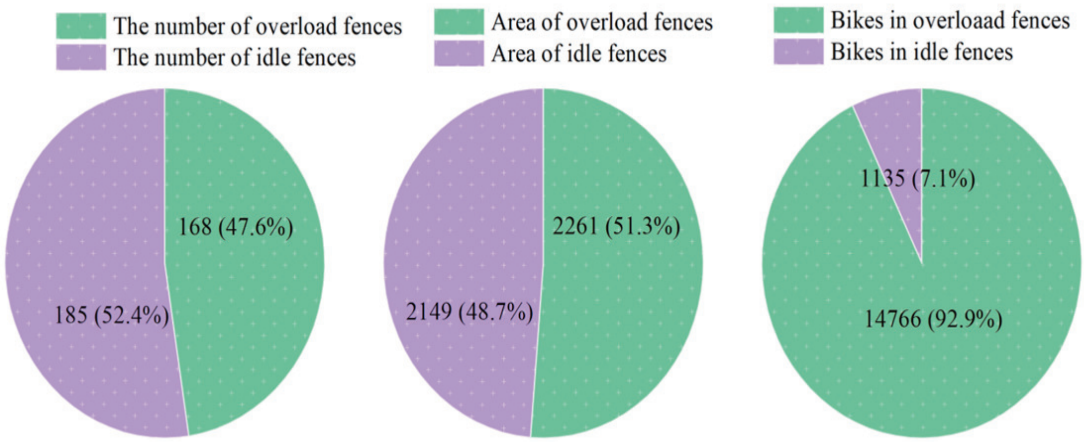


FIGURE 4. The division of 353 fences in the top 40 tidal zones.

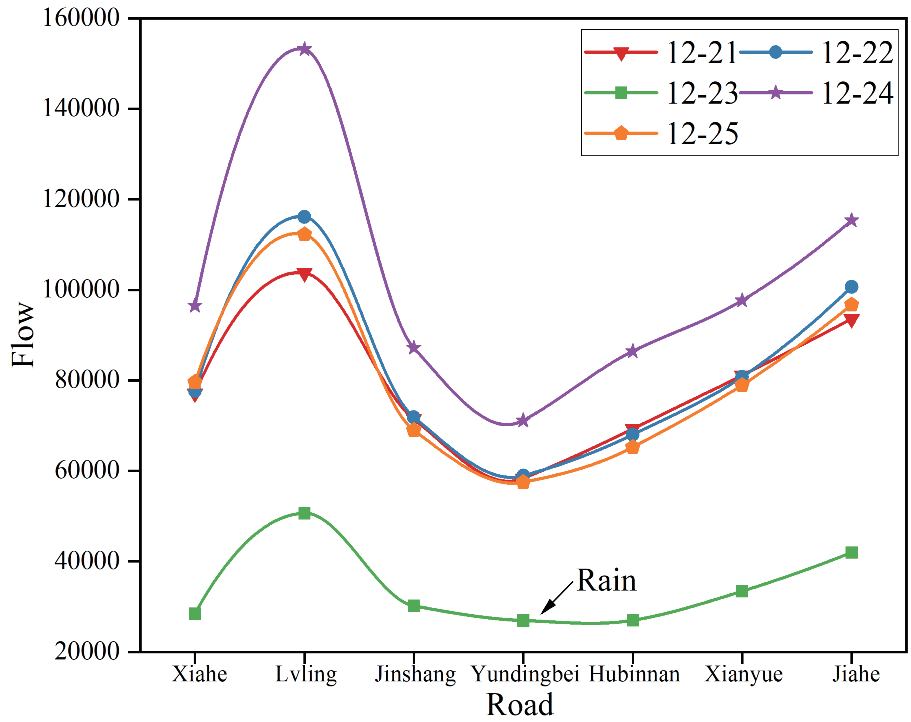


FIGURE 5. The number of bikes on the top seven roads.

5.2.2. *Research on Cycling Environment.* Based on the bikes matched to each road, we obtain the number of bikes on the top seven roads from December 21 to December 25, as shown in Figure 5. The highest number of Lvling Road reached 153,104 on December 24. It is not difficult to find that the cycling volume on December 23 is lower than on the other four days. Due to the sudden drop in temperature on December 23, and the rain, the remaining four days of weather conditions are relatively comfortable, resulting in a significant reduction in the amount of cycling on December 23. Therefore, the weather factor has a great influence on cycling friendliness.

There are also great differences in cycling friendliness between different road sections. For example, Urban tunnel as part of an urban road network, the large gap between the light inside and outside the tunnel cause cyclists to dislike riding in the tunnel section.

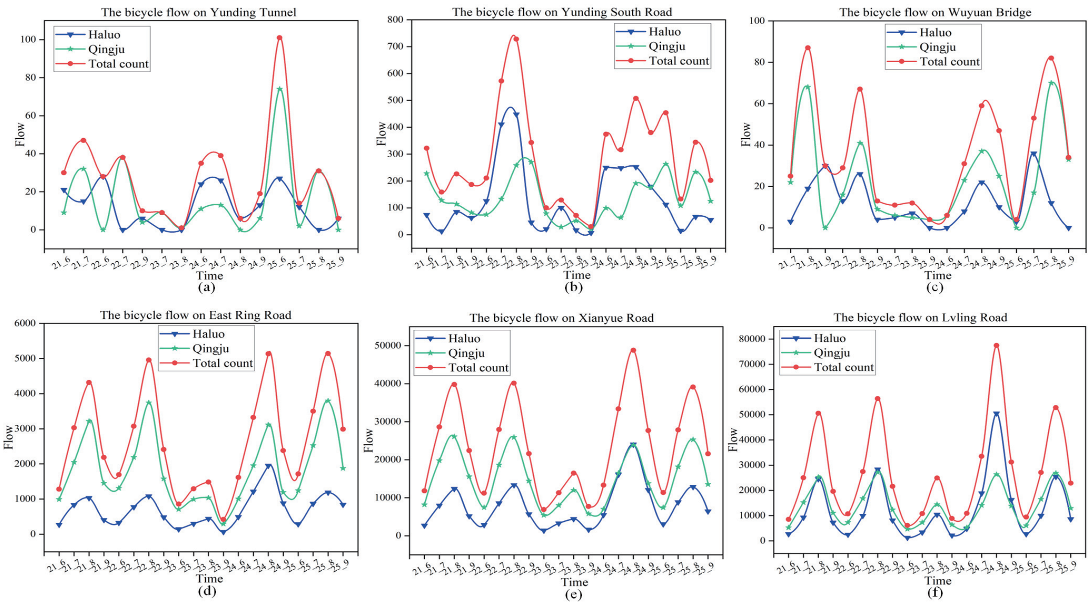


Figure 6. The bicycle flow of different road sections.

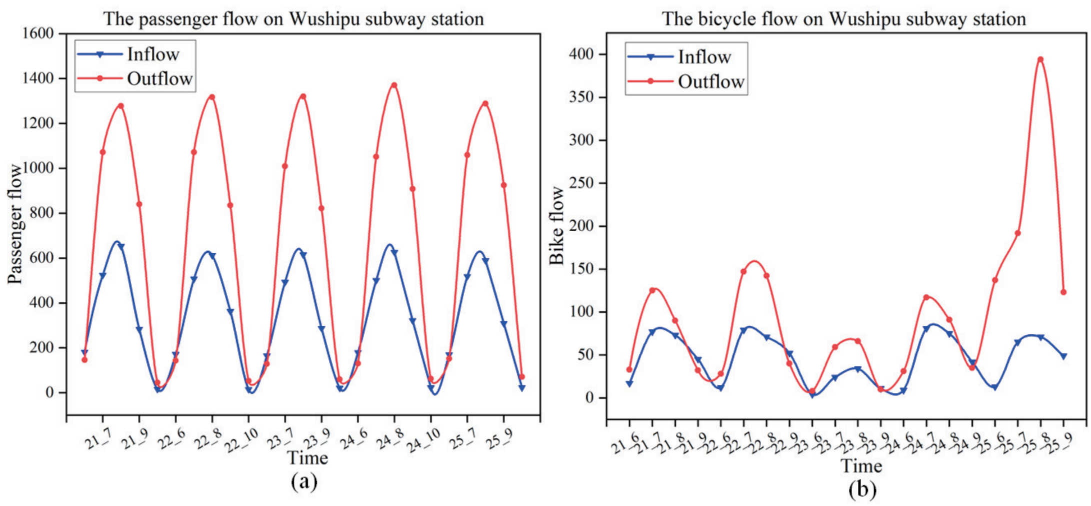


Figure 7. The passenger flow and bicycle flow at Wushipu subway station.

Figures 6(a) and 6(b) show that the bicycle flow of the Yunding Tunnel is less than one-tenth of the whole Yunding South Road. It can be seen that in the tunnel section, the friendliness to cyclists is very low. Moreover, the slope of the bridge will affect the speed of the cyclists, reduce cycling efficiency, and have a certain impact on cycling friendliness. Figures 6(c) and 6(d) show that the bicycle flow on the Wuyuan Bridge is about two percent of the East Ring Road. Therefore, bridge sections have a crucial impact on cycling friendliness. Furthermore, to avoid congestion, cyclists choose to ride in the downtown area. Figures 6(e) and 6(f) show that the bicycle flow on Lvling Road is approximately twice as much as that on Xianyue Road, which can show that cyclists prefer to ride on roads without complicated sections.

Due to People can't reach their destination by subway, the emergence of bike-sharing solves the last-mile problem. Therefore, the subway entrance section is analyzed. This work counts the in-and-out passenger flow and bike-sharing flow of the Wushipu subway station. Figure 7 shows that the outbound passenger flow is about twice the inbound passenger flow, and the bike-sharing outflow is more than the inflow. Especially on December 25, the bike-sharing outflow is much more than the inflow. Therefore, a large number of cyclists in this section may choose to ride to their destination.

The above analysis and research verify the accuracy, effectiveness, and feasibility of the proposed DLBSF system. The system first analyzes the friendliness of the origin and destination of cycling from time and space, solves the tidal phenomenon, and improves the efficiency of renting and parking. The guidance scheme is provided to improve the utilization rate of bike-sharing. Then, the DLBSS system dynamically displays the friendliness of the cycling process to cyclists, who can improve their cycling experience by choosing their best path based on recommendations.

6. **Conclusions.** In this work, we propose a Dockless Bike-sharing friendliness (DLBSF) system, which can dynamically provide cyclists with guidance to comprehensively alleviate the problem of decreasing friendliness. The DLBS recommendation (DLBSR) system optimizes cycling friendliness by first identifying the overload fences where the morning peak tide phenomenon is most prominent, and then provides guidance for cyclists to park the nearest idle fences. The DLBS scoring (DLBSS) system provides the cycling friendliness scheme by scoring and analyzing each road section to improve friendliness.

In future work, we will divide the functional zones, and the Point of Information (POI) may have a crucial impact on cycling friendliness. In addition, bike-sharing station dynamic planning can also improve cycling friendliness.We will further study from POI and bike-sharing station dynamic planning.

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