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DYNAMIC DEMAND FORECAST AND ASSIGNMENT MODEL FOR BIKE-AND-RIDE SYSTEM

ABSTRACT

Bike-and-Ride (B&R) has long been considered as an effective way to deal with urbanization-related issues such as traffic congestion, emissions, equality, etc. Although there are some studies focused on the B&R demand forecast, the influencing factors from previous studies have been excluded from those forecasting methods. To fill this gap, this paper proposes a new B&R demand forecast model considering the influencing factors as dynamic rather than fixed ones to reach higher forecasting accuracy. This model is tested in a theoretical network to validate the feasibility and effectiveness and the results show that the generalised cost does have an effect on the demand for the B&R system.

KEY WORDS

Bike-and-Ride; dynamic demand; generalised cost; user equilibrium model; Frank-Wolfe algorithm;

1. INTRODUCTION

The high level of personal motorisation brings pressure not only to urban traffic but also to the environment and energy [1]. In the past decades, many countries have taken measures to mitigate the pressure, such as developing bike-sharing systems, public transit systems, Park-and-Ride (P&R) systems and Bike-and-Ride (B&R) systems [2].

Among those environmentally friendly transportation systems, B&R system turns out to be faster, more convenient and with a lower cost [3]. As one part of the B&R system, public transport has long been regarded as an effective way of alleviating urban traffic problems for its advantages because of big capacity, low pollution, low energy consumption, and high traffic efficiency. However, the public transport also has its drawbacks, such as its poor flexibility and low ability to provide door-to-door service [4-7]. As the other part of a B&R system, bicycle is substantially faster than walking and more flexible than public transport, but it is not efficient for long-distance trips [8]. Therefore, the B&R system, which combines these two travel modes, provides a way to utilize their advantages and to alleviate the drawbacks from either single system [9-11]. Encouraging people to choose B&R system will have a positive effect in releasing urban transport pressure, reducing traffic pollution, energy consumption and land resource occupation [12, 13].

2. LITERATURE REVIEW

Because of its significant effect on alleviating urban traffic pressure, B&R has attracted a lot of attention. The existing research focused on B&R can be summarized into three main aspects: (1) the analysis of factors affecting the mode choice of B&R and rider behaviour; (2) policies and programs for facility and configuration optimization; (3) demand forecast.

Many studies focused on analysing factors affecting mode choice of B&R. R. Kager, Bertolini [14] provided suggestions on combining bicycle and public transport in a broader perspective, such as higher speed for the bicycle lane and higher public transport capacity. Puello [15] incorporated latent variables and

psychometric data to capture relatively intangible factors that influence the mode choice. Krizek and Stonebraker [16] analysed factors influencing the integration of bicycle and transit, such as transit mode, access, egress distance, and trip purpose. Chen [17] considered the factors affecting the B&R mode choice from three angles: socio-economic characters, trip features and residents' perceptions for the service level of B&R mode. Previous studies also found that bicycle facility is the main factor that influences the mode choice between bicycle and other modes [18-20]. Some researchers explored and found that the weather is also an important factor in the mode choice [21-23]; for instance, the bicycle users may be more sensitive to the rainfall and temperature than other mode users; however, bicycle-friendly facilities can attract riders back to riding. Heinen [24] conducted further exploratory research and found that residents always emphasise the convenience level, the cost and health benefits when deciding on the transportation mode.

Regarding mode choice analysis, Taylor [25] employed a stated preference survey to explore the residents' choice preferences among private cars, P&R mode and the B&R mode. Wardman [26] adopted a multinomial logit model based on the revealed preference and stated preference data, and found that protected non-motorised road or a completely segregated bike path, may encourage more residents to choose the bicycle. There were also some studies that employed the social equilibrium models and mathematical network models [27-29] to explore the B&R mode in terms of bicycle parking locations, bicycle network, route choice, bicycle activity patterns, etc. Yang [30] presented a mode choice model for B&R. Aziz [31] estimated a random parameter (mixed) logit model for active transportation (walking and bicycle) choices for work trips in the New York City. Chan [32] used a Structural Equation Model (SEM) to formulate the relationship between the individual's behavioural intention of using a public bicycle and its influencing factors.

For improving the B&R system, researchers suggested strategies to enhance the ratio of using B&R mode, such as ensuring the parking safety and convenience at the public transport sites, taking the bicycle into public transport management system, giving the bicyclists more right-of-way [33, 34]. Pucher [35] pointed out that the key factors to improve the using rate of B&R are the service level of bicycle transfer facilities and the safety of bicycle parking. Chen [36] explored the correlation between the level of traffic stress (LTS) and bicycle crash by a mixed logit framework and they found that LTS has an effect on injury severity. Pucher [35], Lumsdon [37], and Martens [38] proposed new policies for authorities to improve the use of bicycles, such as infrastructure provisions, supportive land use planning, and restrictions on car use. Another study conducted by Pucher and Buehler [39] found that even though the temperature is much lower in Canada than in America, the usage frequency of bicycles in Canada is higher. Safer biking conditions, and more extensive biking facilities and training programs in Canada may account for this.

A macroscopic forecast method was employed by Zhang [40] to study the situation of bicycle transfer in Beijing and successfully predicted bicycle transfer demand of parking the bike. Caulfield [41] used stated preference survey to do some research on B&R. Recently, with the dramatic increase of sharing bike and rental bike programs in cities, there are many studies focused on demand prediction [42, 43]. For instance, a binary logit model of public bicycles was established by Wu [44] and Chen [45] to predict the demand of public bicycles of the rail transit station. Wardman [46] developed a choice model to identify the factors influencing the rate of cycling to work in the UK and the authors used this model to forecast future trends in urban commuting mode share. Mi [47] considered two factors (travel time and travel cost) in a utility function to build a logit model to get the possibility of bike transfer.

Previous research mentioned above suggested that even though a lot of work has been done in the B&R topic, current research is limited to analysing the factors affecting the traveller's choice and the policies of promoting the B&R system. Although there are some studies focused on the B&R demand forecast, the influencing factors from previous studies are excluded from those forecasting methods. Specifically, the obtained demand was fixed in previous forecasting studies without considering those influencing factors. However, with the change of these influencing factors, the traveller's choice of whether to choose B&R travel mode also varies. In other words, the travel demand of B&R mode changes dynamically rather than being fixed. Thus, there is still a gap in the demand forecast for the B&R system with taking the influencing factors into consideration.

To fill this gap, this paper proposes a new demand forecast model considering the demand of B&R mode as dynamic rather than fixed to reach a higher forecasting accuracy. With specific analysis factors that lead to changes in demand, the entire B&R travel chain was divided into three main processes, and the factors in each process are converted into generalised costs. In this way, the generalised cost is a comprehensive indicator which leads to dynamic changing in demand. The UE model and the adaptive Frank-Wolf algorithm are employed to distribute the dynamic demand of B&R in the network. The proposed non-fixed travel demand in the forecast can provide more realistic prediction and help rational configuration of the B&R facilities (bus stops and bicycle parking lots, etc.) and increase the efficiency of the system.

The following part of this paper is organized as follows: Section 3 explains how to represent the dynamic demand of B&R in the model and introduces the UE model and adaptive Frank-Wolfe algorithm to distribute the dynamic demand of B&R in the network. In Section 4, a theoretical B&R network was designed to validate the feasibility and effectiveness of the proposed framework. Finally, the concluding remarks and limitations are discussed in Section 5.

3. METHODOLOGY

3.1 Combined network of B&R

Public transport and bicycles play different roles in urban transportation due to the difference in their capacity and accessibility. Their roles in urban transportation are shown in *Figure 1*. These two transport modes supplement and collaborate with each other in urban transportation and form the B&R mode. Based on their different functions, the B&R network can be defined as a combined network composed of the public transport network and the bicycle network.
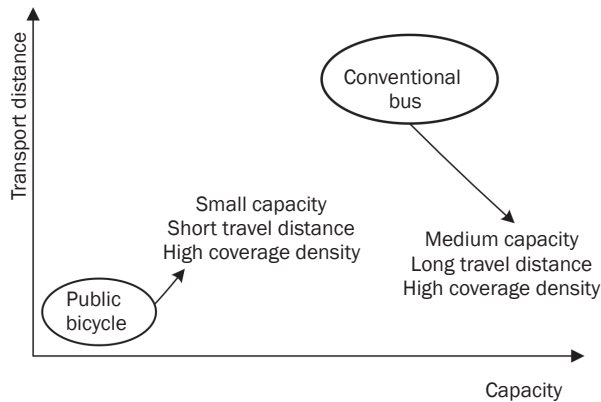

Figure 1 – Different roles in urban transportation

In order to provide a widely applicable model, the conventional bus network and bicycle network were chosen as representatives of the public transport network and the transfer network. The transfer network is an abstract network which mainly reflects the mobility of travellers from the start location of the trip to the bus stop (or from the bus stop to the travel destination). A bicycle and public transport combined network (*Figure 2*) was simulated as G (N, A), in which N is a collection of nodes and A is a collection of network edges. The nodes consist of conventional bus stop N1 and transfer site N2. The transfer site is where a traveller changes their travel mode from bicycle to public transport. The public transport network edge A1, transfer network edge A2 are included in the network edges. The public transport network and the transfer network are connected via transfer sites.
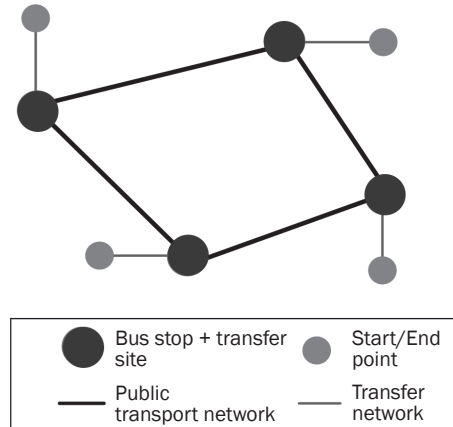

Figure 2 – Bicycle and public transportation network

3.2 Generalised cost

Factors influencing the decision making are usually translated into path impedance or utility. In this study, the generalised cost (negative effect) is used to describe the path impedance. Consequently, the dynamic demand of B&R can be expressed as the response of B&R demand to generalised cost.

From the perspective of a complete B&R travel chain, the entire process can be divided into three main parts: the sub-process of public transport (taking conventional bus as an example), the sub-process of the bicycle, and the sub-process of the transfer between public transport and bicycle. The generalised cost of B&R mode will be analysed from these three sub-processes, respectively. The total generalised cost of the B&R travel is the sum of generalised costs in each stage.

The sub-process of the conventional bus

The generalised cost of the conventional bus consists of the travel time in the bus, waiting time at the bus stop, the impedance for the crowded ride environment and the bus fare. In the algorithm, it can be expressed as follows:

$$u_p^b = \alpha_T^b T_p^b + \alpha_W^b W_p^b + u_o^b \tag{1}$$

where u_p^b is the generalised cost of a conventional bus on route p; α_T^b is the cost of travel time on the bus; α_W^b is the cost of the waiting time for a conventional bus; T_p^b is the travel time for the conventional bus on route p; W_p^b is the waiting time for the conventional bus on route p; u_o^b is the fare for the conventional bus for all routes; u_p^b is the generalised cost for the conventional bus on route p.

For the network description, the Bureau of Public Roads (BPR) function [48], which is set by the U.S. Federal Highway Administration, is often used as an impedance of the road segment. This function can also be used in the B&R research. In general, the road

traffic condition and the passenger flow are the two main factors related to the conventional bus travel time. Therefore, it can be shown as:

$$T_p^b = t_p^0 \left[1 + \alpha_1 \left(\frac{v_{il} + v_{il}'}{K_b^l} \right) \right], \ i \in S \qquad (2)$$

where T_p^b is the travel time for the conventional bus on route p; i is a random bus station on route p; t_p^0 is the initial travel time of conventional bus which is affected by the road condition, and it can be obtained from the actual GPS data of public transportation vehicles; v_{il} is the number of passengers who get on the bus before bus stop i and get off the bus after bus stop i; v_{il}' is the number of passengers who get on the bus after bus stop i; K_b^l is the capacity of the conventional bus line l; α_1 and β_1 are the travel time parameters of the bus. S is the set of bus stations.

According to the Welding model [49, 50], when the passenger arrives at the bus stop randomly, the passenger's expected waiting time is the sum of the half of the bus headway and the coefficient of variation of the bus headway. The waiting time at the bus stop can be shown as:

$$W_p^b = \frac{0.5}{f_s^{rl}} 1 + (CV^2) \qquad (3)$$

where W_p^b is the waiting time at the bus stop; f_s^{rl} is the departure frequency of line l at station s. CV is the headway variation coefficient. The headway time variation coefficient CV can be obtained by calculating the sample mean and biased deviation based on the actual headway distribution. CV can be predicted by assuming a distribution function.

The sub-process of the bicycle

Compared to the conventional buses, bicycles can serve immediately but need to consume some physical strength. Considering the factors that mainly affect the traveller's bicycle choice, such as cycling time, rental expenses and physical energy consumption, the generalised cost of bicycle travel on route p can be expressed as:

$$u_p^{pb} = \alpha_t^{pb} T_p^{pb} + \alpha_y^{pb} Y_p^{pb} + u_0^{pb} \qquad (4)$$

where u_p^{pb} is the generalised cost of bicycle travel on route p; α_t^{pb} is the cycling cost; T_p^{pb} is the travel time on a bicycle on route p; α_y^{pb} is the parameter of physical energy consumption; Y_p^{pb} is the parameter of fatigue caused by cycling on route p; u_0^{pb} is the fee for renting a bicycle for all routes.

Travel time (T_p^{pb}) can be obtained from the length of route and the riding speed:

$$T_p^{pb} = \frac{L_p}{V_p^{pb}} \qquad (5)$$

where T_p^{pb} is the travel time of riding on route p; L_p is the length of riding on route p; V_p^{pb} is the average speed of riding on route p.

The consumption of physical energy can be estimated according to its relationship with the travel time. As the travel time increases, the physical consumption also increases. The physical fatigue parameter can be expressed as a function of the travel time. In this paper, the Binomial function studied by Gong [51] is employed:

$$Y_p^{pb} = f(T_p^{pb}) = \tau_1 T_p^{pb} + \tau_2 (T_p^{pb})^2 \qquad (6)$$

where Y_p^{pb} is the consumption of physical energy; τ_1 and τ_2 are parameters of the function and can be determined according to a specific situation. It can be seen from the function that the physical consumption value increases with the increase of the distance. This can explain why bicycles are not suitable for long-distance trips.

The sub-process of transfer

In the transfer stage, the transfer time includes the walking time, the waiting time and the delay. The waiting time has been considered in the above two sub-processes. The walking time and the delay are two main factors that need to be discussed in this sub-process. The walking time refers to the consumption of time in the process of completing the transfer between the bicycle and the public transport on foot. The delay represents the uncertainty that may be caused by the mode conversion and the subjective reluctance of the traveller, which is the inherently general cost of the transfer. The generalised cost for transfer is:

$$u_p^t = \alpha_z^t Z_p^t + u_0^t \qquad (7)$$

where u_p^t is the generalised cost; α_z^t is the unit time value; Z_p^t is the walking time during the transfer process; u_0^t is the inherent generalised cost of transfer between bicycle and bus; u_p^t is the generalised cost for transfer on route p.

The assignment method for this study is based on the route rather than the road segments. A variety of public transportation modes can be included in one route. This paper only selects the conventional bus as a generalised research object. The function of the generalised cost of route p for an arbitrary Origin Destination pair (OD) (r, s) is:

$$u_p^{rs} = \sum_{a \in A_t \cup A_d} \delta(p,a) u_a \qquad (8)$$

where u_p^{rs} is the generalised cost of route p for an arbitrary OD pair r and s; when the road segment a is on route p which is between OD pairs r and s, $\delta(p,a)$=1, otherwise, $\delta(p,a)$=0; u_a is the generalised cost for road augment; A_t represents the public transport network and A_d is the bicycle network.

3.3 Model description

The forecast and assignment of B&R demand are the basis for optimizing the configuration of the B&R system. The generalised cost of B&R will affect the

travel demand of B&R mode and make the travel flow shift in the transportation network. Therefore, the dynamics of the travel demand is directly related to the generalised cost. In order to optimize B&R network configuration and improve traffic efficiency, it is very necessary to build a dynamic traffic assignment model with taking the generalised cost into consideration. The UE model which is based on the Wardrop's first principle [52] has been used in the traffic network analysis. In the traditional traffic assignment issue, the travel demand is always assumed to be known and fixed. However, it is difficult to accurately describe the actual demand in the network. In this paper, the UE model is employed as the basic model and takes the generalised cost as a dynamic factor to build a more accurate demand forecast model for the B&R system.

Based on the analysis of the generalised cost, the change of the generalised cost is the change of impedance. With the increase of impedance, the probability that the traveller chooses to travel by bicycles and public transportation becomes smaller. Conversely, with the reduction of impedance, the travellers are more inclined to choose the B&R mode, so the demand for B&R becomes larger. Consequently, the form of a negative exponential function was used to represent this feature.

$$Q_r = Q \cdot e^{-\alpha\mu} \qquad (9)$$

where Q is the maximum potential travel demand; Q_r is the actual travel demand under a certain generalised travel cost; μ is the generalised cost in a trip; α is a dynamic demand parameter, which reflects the sensitivity of the traveller to the generalised cost; the specific value of a parameter can generally be determined through investigation.

A higher traffic demand brings busy traffic and busy traffic means higher route impedance. When the route impedance increases, the traveller may cancel some of the originally planned trips or change their destination, so the traffic demand between the original OD pairs will be reduced accordingly. The travel demand and the route impedance interact with each other, and eventually, they will reach an equilibrium state.

In this issue, the amount of travel between two OD pairs, (r,s), is actually related to the impedance between the two points. The reason may be that the traveller with a travel plan changes their plan or cancels the plan directly, due to the fact that the available attraction points are all difficult to reach. Consequently, it not only affects the assignment of travel demand, but also the generation of travel. For the basic UE model, it is assumed that the amount of travelling between each pair of the OD pairs is fixed. In other words, it would not be affected by the impedance. In contrast, the UE model with considering of generalised cost treats that demand as a variable.

The relationship between the travel demand of a pair of OD points and the route impedance can be described by a function:

$$q_{rs} = D_{rs}(u_{rs}^{min}) \quad \forall r,s \qquad (10)$$

where D_{rs} is a demand function with u_{rs}^{min} as a variable; u_{rs}^{min} is the minimum impedance from r to s; q_{rs} is the travel demand between r and s.

Generally speaking, the demand function between all OD pairs has a substantially consistent form, except that the specific parameters of the heterogeneous pairs are different. These parameters are determined by the size of the population, their income, and car ownership in a specific trip generation zone, as well as the employment status, the ability to attract activities such as shopping and tourism. According to the dynamic demand analysis in the previous section, the travel demand function takes the form of a negative index:

$$q_{rs} = Q_{rs} \cdot \exp(-a \cdot u_{rs}^{min}) \qquad (11)$$

where Q_{rs} is a potential demand function, and parameter, a is related to the traffic analysis zone and used to characterise land use characteristics. Additionally, the demand function should be bounded because the amount of population and vehicles in a zone are limited. There is a constraint for this function:

$$0 \leq q_{rs} \leq Q_{rs} \qquad (12)$$

Similar to the normal equilibrium model, the UE problem of dynamic demand can be described by the following model:

$$\min: Z(X,q) = \sum_a \int_0^{x_a} u_a(w)\,dw - \sum_{rs} \int_0^{q_{rs}} D_{rs}^{-1}(w)\,dw$$

$$\text{s.t. } 0 \leq q_{rs} < Q_{rs}$$
$$f_k^{rs} \geq 0, \quad \forall r,s$$
$$\sum_k f_k^{rs} = q_{rs} = \quad \forall r,s \qquad (13)$$
$$x_a = \sum_{r,s}\sum_k f_k^{rs} \cdot \delta_{a,k}^{rs}, \quad \forall a$$
$$\delta_{a,k}^{rs} = \begin{cases} 1, & \text{section } a \text{ is on path } k \text{ between } r \text{ and } s \\ 0, & \text{others} \end{cases}$$

where x_a is the traffic flow on section a; $u_a(w)$ is the function of impedance; q_{rs} is the travel demand between r and s; $D_{rs}^{-1}(w)$ is the inverse function of travel demand; Q_{rs} is a potential demand function; f_k^{rs} is the traffic flow on the k-th path between r and s; $\delta_{a,k}^{rs}$ is a section path-related variable.

3.4 Adopted Frank-Wolfe algorithm

Frank-Wolfe algorithm is employed to optimise the solution in the model as described by Cho et al. [53]. Firstly, the objective function of the model is changed into another form with the route flow as a variable. The algorithm is also assumed to have been iterated

n times. Corresponding to the traffic flow of route f^n, the traffic flow of road segments and travel demand are x^n and q^n, respectively. In order to obtain the iteration direction of the objective function, the model was decomposed into multiple independent sub-problems corresponding to each OD point pair. When all sub-problems are solved, the corresponding road segment flow and the OD demand are generated. Optimal iteration step value λ can be obtained based by dichotomy based on the traffic flow of the road segment and OD demand:

$$\text{min}: Z(\lambda) = \sum_a \int_0^{x_a^n + \lambda(y_a^n - x_a^n)} u_a(w)dw - \sum_{rs} \int_0^{q_{rs}^n + \lambda(p_{rs}^n - q_{rs}^n)} D_{rs}^{-1}(w)dw \quad (14)$$

where parameter λ meets the restriction: $0 \le \lambda \le 1$; x_a^n is road segment flow after n times iteration; y_a^n is additional traffic after n times iteration; q_{rs}^n is travel demand after n times iteration; p_{rs}^n is additional demand after n times iteration.

The updated traffic flow of the road segment and OD demand can be obtained by:

$$x_a^{n+1} = x_a^n + \lambda(y_a^n - x_a^n) \quad (15)$$

$$q_{rs}^{n+1} = q_{rs}^n + \lambda(p_{rs}^n - q_{rs}^n) \quad (16)$$

The algorithm for solving the user equilibrium model of the B&R network under dynamic demand is as follows and the process is shown in *Figure 3*:

1) *Initialization.* In this step, we initialize $n=1$. Firstly, the network is extended to a combined network of bus networks and bicycle networks. Then, a set of road segment traffic flow, $\{x_a^0, \forall a\}$, and OD demand, $\{q_{rs}^1, \forall a, s\}$, that satisfy the constraints of the model need to be set. For example, $\{x_a^0 = 0, \forall a\}$ was assumed in this paper, then, determine q_{rs}^1 based on the maximum OD travel demand Q_{rs} (e.g. $q_{rs}^1 = \frac{Q_{rs}}{2}$). Finally, according to All or Nothing (AON) algorithm, q_{rs}^1 is assigned on the network with a road segment traffic flow $\{x_a^0, \forall a\}$.

2) *Update the impedance for each edge of the network.* Calculate the value of $D_{rs}^{-1}(q_{rs}^n)$, based on the function $u_a^n = u_a(x_a^n) \forall a$.

3) *Next iteration.* Calculate the shortest path and minimum impedance c_{rs}^n between OD pairs (r, s) based on $\{u_a(x_a^n): \forall a\}$, and consider the following
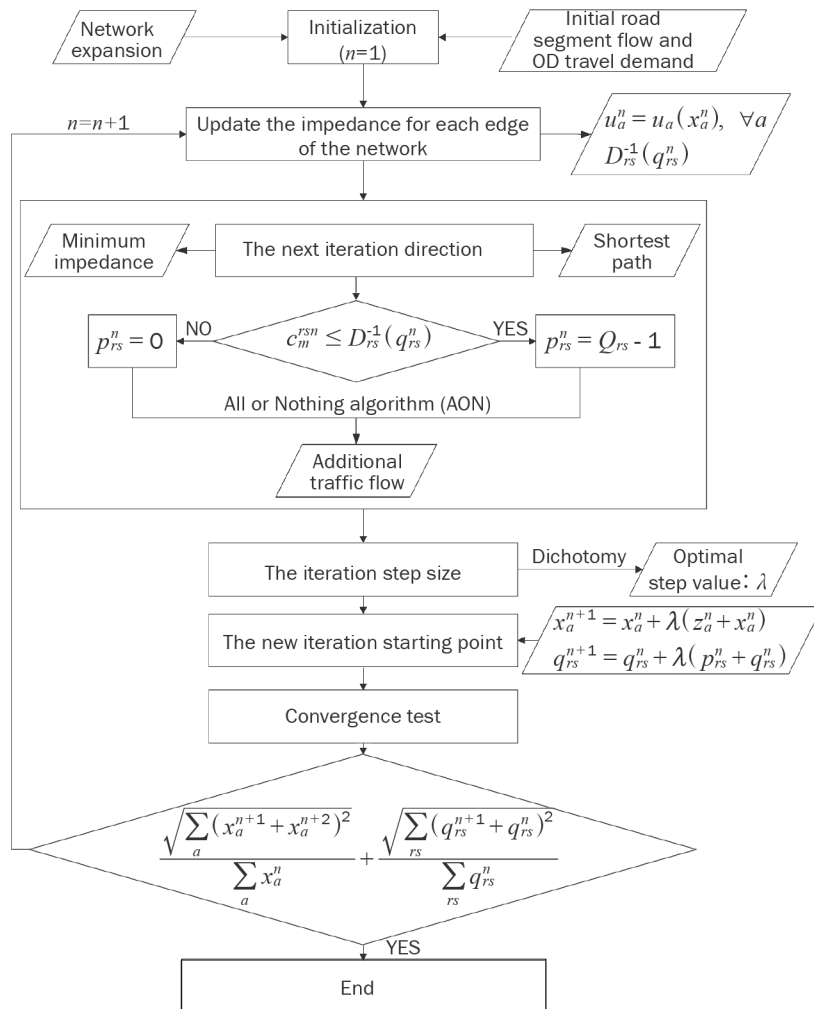

Figure 3 – Process of algorithmic solution

situation to determine the additional traffic: (i) $c_m^{rsn} \leq D_{rs}^{-1}(q_{rs}^n)$: let $p_{rs}^n = Q_{rs}$-1 and assign p_{rs}^n to the shortest path with All or Nothing (AON) algorithm and correspondingly increase the additional traffic z_a^n of each road segment on the shortest path; (ii) $c_m^{rsn} > D_{rs}^{-1}(q_{rs}^n)$: let $p_{rs}^n = 0$ and, consequently, the additional traffic of each road segment on the shortest path is unchanged.

4) *Determine the step value for iteration*. Use the dichotomy to find the optimal value λ.

5) *Determine the new iteration starting point* with the following function: $x_a^{n+1} = x_a^n + \lambda(z_a^n - x_a^n)$, $q_{rs}^{n+1} = q_{rs}^n + \lambda(p_{rs}^n - q_{rs}^n)$.

6) *Test convergence*. If the result meets the following restriction, the calculation would be stopped; else return to Step 2 and let $n = n+1$.

$$\frac{\sqrt{\sum_a (x_a^{n+1} - x_a^n)^2}}{\sum_a x_a^n} + \frac{\sqrt{\sum_{rs} (q_{rs}^{n+1} - q_{rs}^n)^2}}{\sum_{rs} q_{rs}^n} < \varepsilon$$

where ε is a predetermined small positive number.

7) *End of the algorithm*.

4. MODEL SIMULATION

4.1 The description of simulated B&R network

In this simulation, a simulated B&R network was constructed. Based on the simplified public transport network, a B&R network was constructed as shown in *Figure 4*. The example network consists of 17 nodes, 20

edges, and 8 OD pairs. The bus lanes in this network are all bidirectional. The square node is the starting point, and the round node is the bus stop. To simplify the structure of the network and the process of calculation, this paper makes some assumptions as follows:

i) The distance between the bicycle parking lot and the bus stop (starting/end point) is 0.

ii) The capacity of the road between the two bus stops is 700 persons/hour and the capacity of the transfer road (the road between the start point/end point and the bus stop) is 3,000 persons/hour.

iii) The initial impedance of roads between bus stops is assumed in *Table 1*.

iv) The potential travel demand between each OD pair and the dynamic demand parameter a for the function of dynamic demand, $Q_r = Q \cdot \exp(-a \cdot t)$, is also assumed in *Table 2*.

4.2 Simulation

Based on the analysis in the previous chapter, the model can be executed in the following steps.

As shown in *Figure 4*, the original OD points are the nodes that coincide with the bus stop. Therefore, it is necessary to extend those nodes to obtain new OD points and make assumptions about whether the traveller would use a bicycle as a transfer vehicle at these new OD points (*Table 3*).

Based on the extended nodes, the impedance and capacity assumed previously, the extended adjacency matrix can be obtained (*Table 4*).

Table 1 – Initial impedance of roads between bus stops

Node	1	2	3	4	5	6	7	8	9
1	0	2	—	2	—	—	—	—	—
2	1	0	4	—	3	—	—	—	—
3	—	3	0	—	—	2	—	—	—
4	3	—	—	0	1	—	4	—	—
5	—	2	—	2	0	2	—	1	—
6	—	—	3	—	3	0	—	—	—
7	—	—	—	3	—	—	0	5	—
8	—	—	—	—	2	—	4	0	2
9	—	—	—	—	—	3	—	2	0

Table 2 – Assumed parameters in this model

Start point	1	2	3	4	6	7	8	9
End point	9	8	7	6	4	3	2	1
Potential demand	1,000	900	800	950	880	920	700	960
Dynamic demand parameter (*a*)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 3 – Original OD point and extended node

Original OD point	1	2	3	4	6	7	8	9
Extended node	10	11	12	13	14	15	16	17
Bicycle	1	0	1	1	0	1	1	0
Impedance	1	3	1	1	3	1	1	3
Capacity	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000

Note: The value for the bicycle is defined in that if a traveler uses bicycle as transfer vehicle, its value is 1, otherwise, its value is 0.

Table 4 – Extended adjacency matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	2	0	2	0	0	0	0	0	1	0	0	0
2	1	0	4	0	3	0	0	0	0	0	3	0	0
3	0	3	0	0	0	2	0	0	0	0	0	1	0
4	3	0	0	0	1	0	4	0	0	0	0	0	1
5	0	2	0	2	0	2	0	1	0	0	0	0	0
6	0	0	3	0	3	0	0	0	2	0	0	0	0
7	0	0	0	3	0	0	0	5	0	0	0	0	0
8	0	0	0	0	2	0	4	0	2	0	0	0	0
9	0	0	0	0	0	3	0	2	0	0	0	0	0
10	1	0	0	0	0	0	0	0	0	0	0	0	0
11	0	3	0	0	0	0	0	0	0	0	0	0	0
12	0	0	1	0	0	0	0	0	0	0	0	0	0
13	0	0	0	1	0	0	0	0	0	0	0	0	0

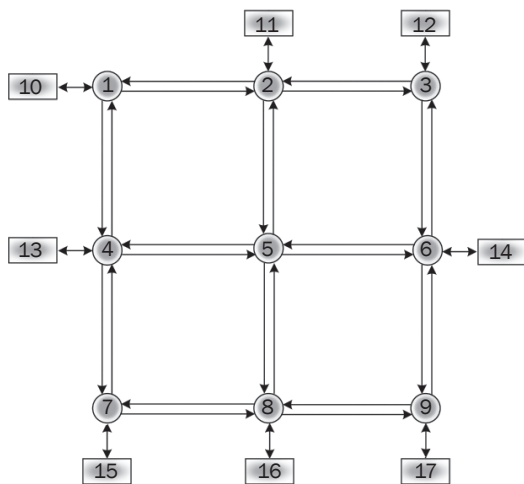*Note: Some nodes have been omitted due to layout reasons*

Figure 4 – Combined network of bus and bicycle

Table 5 – The shortest path and smallest impedance

r	s	The shortest path	The smallest impedance
10	17	10-1-4-5-8-9-17	10
11	16	11-2-5-8-16	8
12	15	12-3-6-9-8-7-15	12
13	14	13-4-5-6-14	7
14	13	14-6-5-4-13	9
15	12	15-7-4-5-6-3-12	11
16	11	16-8-5-2-11	8
17	10	17-9-8-5-2-1-10	11

According to the extended adjacency matrix and extended capacity matrix, together with the function of impedance and traffic flow, $t = W \cdot \left(1 + 0.15 \cdot \left(\frac{X_1}{C_{max}}\right)^4\right)(X_1 = 0)$, the impedance matrix of road segment can be obtained (*Table 4*).

Based on the impedance matrix of the road segment, OD points and Dijkstra's algorithm, the shortest path and the smallest impedance can be obtained (*Table 5*).

Based on the dynamic demand function, $Q_r = Q \cdot \exp(-a \cdot t)$, where a is the dynamic demand parameter, t is the smallest impedance, the actual travel demand can be obtained (*Table 6*).

Then, the All or Nothing (AON) algorithm was employed to assign the actual demand to the shortest path. Then, the assigned travel flow after the first assignment process can be obtained (*Table 7*).

The next job is updating the impedance of each segment to find the following iteration direction, and determining the addition flow based on different constraints. The iteration step size is determined by using the dichotomy. Following these, the new iteration start point can be obtained.

Finally, with the end of the iterations and convergence test, the final assignment result can be obtained (*Tables 8-10*). The traffic demand of B&R with considering the generalised cost can be assigned as shown in *Figure 5*.

Table 6 – Result of dynamic demand

Start point – end point	10-17	11-16	12-15	13-14	14-13	15-12	16-11	17-10
Q	1,000	900	800	950	880	920	700	960
Smallest impedance (t)	10	8	12	7	9	11	8	11
Dynamic demand parameter (a)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Q_r	904.8	830.8	709.5	885.8	804.3	824.2	646.2	860.0

Note: A unified value for a is assumed as 0.01.

Table 7 – Assigned travel flow of the first assignment process

Node	1	2	3	4	5	6	7	8	9	10	11
1	0	0	0	904.8	0	0	0	0	0	860.0	0
2	860.0	0	0	0	830.8	0	0	0	0	0	646.2
3	0	0	0	0	0	709.5	0	0	0	0	0
4	0	0	0	0	2,614.8	0	0	0	0	0	0
5	0	1,506.2	0	804.3	0	1,709.9	0	1,735.6	0	0	0
6	0	0	824.2	0	804.3	0	0	0	709.5	0	0
7	0	0	0	824.2	0	0	0	0	0	0	0
8	0	0	0	0	1,506.2	0	709.5	0	904.8	0	0
9	0	0	0	0	0	0	0	1,569.5	0	0	0
10	904.8	0	0	0	0	0	0	0	0	0	0
11	0	830.8	0	0	0	0	0	0	0	0	0

Note: Some nodes have been omitted due to layout reasons

Table 8 – Final assignment of traffic flow of road segment

Node	1	2	3	4	5	6	7	8	9	10	11
1	0	182.5	0	665.3	0	0	0	0	0	588.1	0
2	820.2	0	96.1	0	654.9	0	0	0	0	0	342.9
3	0	256.8	0	0	0	243.1	0	0	0	0	0
4	78.4	0	0	0	1,358.4	0	241.2	0	0	0	0
5	0	923.6	0	614.4	0	916.9	0	1,086.6	0	0	0
6	0	0	449.1	0	612.9	0	0	0	235.6	0	0
7	0	0	0	520.2	0	0	0	0	0	0	0
8	0	0	0	0	915.3	0	233.7	0	534.4	0	0
9	0	0	0	0	0	15.6	0	805.2	0	0	0
10	537.2	0	0	0	0	0	0	0	0	0	0
11	0	551.3	0	0	0	0	0	0	0	0	0

Table 9 – Final OD demand

Start Point	10	11	12	13	14	15	16	17
End Point	17	16	15	14	13	12	11	10
Demand	877.29	821.73	706.76	861.39	801.497	800.19	635.69	839.77

Table 10 – Final minimum impedance

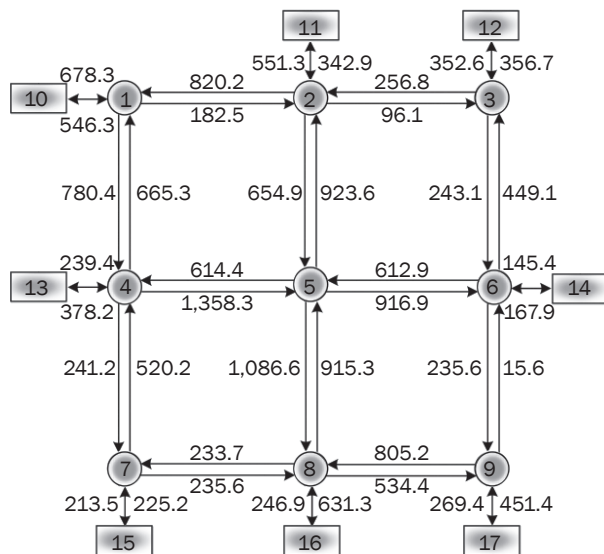| Start Point	10	11	12	13	14	15	16	17
End Point	17	16	15	14	13	12	11	10
Minimum Impedance	13.224	9.187	12.516	9.888	9.436	14.094	9.733	13.516

Figure 5 – Optimized traffic flow assignment

5. CONCLUSION

This study proposes a dynamic demand forecast and assignment model to predict the demand of the B&R system more accurately, help rationally configure the B&R facilities (bus stops and bicycle parking lots, etc.) and increase the efficiency of the system. In this paper the B&R process has been divided into three main sub-processes and the effective factors in each sub-process have been transferred into the generalised cost so that the change of the B&R demand was reflected by the change of generalised cost. For modelling this process, this paper introduced a UE model that adopted the Frank-Wolfe algorithm to optimize the solution in the model. Finally, the proposed method was verified by a simulation on a theoretical network. The research framework reflects the response of the B&R demand to generalised cost more realistically by the non-fixed demand forecasting process, which could help decision makers and engineers to design the B&R facilities without unnecessary losses.

There are also some limitations in this work, (1) it only considers the conventional buses as representative public transport in the B&R system that is composed of many kinds of traffic modes in reality; (2) it does not consider all the factors that have an impact on the generalised costs, other important factors such as distance from origin to bus stop, delay and frequency of public transport that can also make difference to the generalised cost. Future studies can extend to the dynamic demand of the B&R focus on those domains.

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自行车和公共交通联合出行动态需求预测和分配模型

摘要：

自行车和公共交通联合出行(B&R)一直以来都被认为是解决诸如城市交通拥堵、尾气排放、出行公平等问题的有效途径。尽管许多学者在B&R的需求预测方面进行了大量的研究，但是所用的需求预测模型中缺少对影响出行者B&R方式选择的影响因素的考虑。为了提高需求预测的准确性，在分析影响出行者B&R方式选择因素的基础上，本文将B&R的需求视为动态变化的而非固定的量，提出了一个新的B&R动态需求预测和分配模型。为验证模型的可行性和有效性，本文将该模型在抽象网络中进行了测试，结果表明广义成本确实对B&R方式的需求产生了影响。

关键词：自行车与公共交通联合出行；动态交通需求；广义费用；用户均衡模型；FRANK-WOLFE算法；

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