Capacity Estimation of Mid-block Bicycle Lanes with Mixed Two-Wheeled Traffic

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by Lu Bai, Pan Liu, N.N. Sze, Ching-Yao Chan and Huaguo Zhou

ABSTRACT: The primary objective of this study was to propose a procedure for estimating the capacity of mid-block bicycle lanes considering different types of two-wheeled vehicles. The focus was on the uninterrupted-flow mid-block bicycle lanes on urban streets. Data were collected at five mid-block bicycle lanes in Nanjing, China. Composite headway distribution models were developed to identify the headway distributions of e-bikes, e-scooters and bicycles. The headway distribution of the overall two-wheeled vehicles was estimated by aggregating the headway distributions of e-bikes, e-scooters and bicycles considering their proportions in a bicycle lane. A distribution-free estimation approach was followed to determine the key parameters of the composite headway distribution models. A procedure was then proposed for estimating the capacity of mid-block bicycle lanes with mixed two-wheeled traffic. The proposed procedure was validated using field data, and the results suggested that the proposed procedure provides reasonable estimates for the aggregated capacity of mid-block bicycle lanes. The estimated capacity of a mid-block bicycle lane for e-bikes, e-scooters and bicycles was 3,757, 3,804 and 2,791 bicycles/h, respectively, and the aggregated capacity of a mid-block bicycle lane was 3,332 bicycles/h. The bicycle equivalent factor for e-bikes and e-scooters with respect to bicycles was 0.7429 and 0.7337, respectively. The proposed capacity estimation procedure can be directly used for estimating the capacity of mid-block bicycle lanes with varying geometric design characteristics and traffic compositions.

Keywords: e-bike, e-scooter, bicycle, bicycle lane, capacity, composite headway distribution

1. INTRODUCTION

The number of electric bicycles has increased dramatically during the past decade in China. Two types of electric bicycles are currently being used, including bicycle style electric bicycles (e-bikes) and scooter style electric bicycles (e-scooters). E-bikes are similar to regular bicycles in terms of their size and weight. They are usually equipped with 36-Volt batteries and 180 to 250-Watt motors. E-scooters are more similar to motorcycles, and are usually installed with 48-Volt batteries and 350 to 500-Watt motors (Cherry and Cervero, 2007; Lin et al, 2008). In China, both e-bikes and e-scooters are legally classified as bicycles, and are required to be operated in traditional bicycle lanes. The presence of different types of two-wheeled vehicles results in mixed traffic flow in bicycle lanes, generating complex environment for cycling. A critical question arises: how two-wheeled vehicles with distinct operational characteristics influence the capacity of mid-block bicycle lanes?

Capacity is an essential factor that is used for planning, design, monitoring, prioritization and strategizing of mid-block bicycle lanes. According to the Highway Capacity Manual (HCM), capacity represents the maximum sustainable hourly flow rate at which persons or vehicles can be expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, environmental, traffic, and control conditions (HCM, 2010). Previous studies have considered two different conditions: (a) the capacity of uninterrupted-flow bicycle facilities, such as the exclusive and shared bicycle lanes that are physically separated from vehicular lanes and do not have fixed interruptions; and (b) the capacity of interrupted-flow bicycle facilities, such as the on-street bicycle lanes that pass through intersections (Allen, 1998a, 1998b; Raksuntorn and Khan, 2003; Wang et al, 2011a, 2011b). In the HCM, the capacity of uninterrupted-flow bicycle facilities was measured as the flow rate during the most heavily traveled 15 minutes of peak periods, while the capacity of interrupted-flow bicycle facilities was estimated on the basis of the saturation flow rate and the ratio between the effective green time and cycle length at signalized intersections, and the distribution of vehicle headways at unsignalized intersections (HCM, 2000, 2010; Opiela et al, 1980).

Previous studies have indicated that the space provided to cyclists heavily affects the capacity of bicycle lanes (HCM, 2000, 2010). The American Association of State Highway and Transportation Officials (AASHTO) recommended that the minimum width of an on-street bicycle lane should be 1.5 m (AASHTO, 1991). The HCM recommended that the width of a two-lane cycleway should be 2.4 m, and the width of a three-lane cycleway should be 3.0 m (HCM, 2000). The Separated Bike Lane Planning & Design Guide (SBLPDG) published by the Massachusetts Department of Transportation recommended that the width of the bike lane zone should be 3.0 m for one-way separated bike lanes with high volumes of bicyclists, while in constrained conditions the minimum width of the bike lane zone should be 2.4 m (SBLPDG, 2015). In China, the Code for Design of Urban Road Engineering (CDURE) recommended that a cycleway should contain at least two bicycle lanes, and the total width should not be less than 2.5-m wide (CDURE, 2012).

The estimated capacity of bicycle lanes varies greatly in different countries, mainly because the widths of bicycle lanes are different. Botma suggested that the capacity of a 2.5-m wide bicycle lane was 9000 bicycles/h in Netherlands (Botma and Papendrecht, 1991). Homburger reported that the capacity of a 1.0-m wide bicycle lane was approximately 2600 bicycles/h in Davis in the United States (Homburger, 1976). The HCM recommended a saturation flow rate of 2000 bicycles per hour per lane for a one-directional bicycle lane under interrupted-flow conditions in the United States (HCM, 2010). Previous studies in China have suggested that the capacity of a bicycle lane varied between 1400 and 2100 bicycles per hour per meter (Jin et al, 2015; Liu et al, 1993; CDURE, 2012). The CDURE suggested that the capacity of a 1.0-m wide bicycle lane that was separated from motor traffic was between 1600 and 1800 bicycles/h, and the capacity of a 1.0-m wide bicycle lane that was not separated was between 1400 and 1600 bicycles/h (CDURE, 2012).

Despite all the efforts that have been made, little documentation has focused on the capacity of a bicycle lane with mixed two-wheeled traffic. The operational characteristics of e-bikes, e-scooters, and bicycles are different, leading to distinct behavioral characteristics of their riders (Cherry and He, 2010; Guo et al, 2014; Lin et al, 2008; Wu et al, 2010; Yang et al, 2015; Zhang and Wu, 2013). The current design standards and guidelines mainly focus on the characteristics of regular bicycles. Without taking into account the distinct behavioral characteristics of e-scooter, e-bike and regular bicycle users, the capacity estimates of bicycle lanes could be seriously biased.

The primary objective of the study was to propose a procedure for estimating the capacity of mid-block bicycle lanes considering different types of two-wheeled vehicles. The focus was on the uninterrupted-flow mid-block bicycle lanes on urban streets. Figure 1 depicts the basic research framework of this study. Composite headway distribution models were used for identifying the distributions of the unconstrained and constrained headways for e-bikes, e-scooters and bicycles. With the composite headway distribution models, we estimated the capacity of mid-block bicycle lanes with mixed two-wheeled traffic flow, and proposed a procedure for determining the capacity of mid-block bicycle lanes given the proportions of different types of two-wheeled vehicles.

The paper is an extension of our previous paper presented in the 96th annual meeting of the Transportation Research Board (Bai et al, 2017). In this paper, we defined the headways of two-wheeled vehicles in mid-block bicycle lanes, and identified the correlations between the widths and the aggregated capacity of mid-block bicycle lanes. We also evaluated the effects of the proportions of e-bikes, e-scooters and bicycles on the distribution of the headways of two-wheeled vehicles and the aggregated capacity of mid-block bicycle lanes. Based on the research results, we proposed a procedure for determining the capacity of mid-block bicycle lanes given the proportions of different types of two-wheeled vehicles; and validated the proposed capacity estimation method based on field data. We expect that the research results will help traffic engineers develop design standards and guidelines to improve the operations of mixed two-wheeled traffic flow in a bicycle lane. The research results may also provide traffic management authorities with insights to establish policies or regulations regarding the use of electric bicycles.

2. COMPOSITE HEADWAY DISTRIBUTION MODEL

The composite headway distribution model was originally developed by Buckley (1968), and was later used to identify car following behaviors and estimate the speed distribution of free-moving automobiles (Hoogendoorn and Bovy, 1998; Wasielewski, 1979). The composite headway distribution model rests on the assumption that the vehicles in a traffic stream can be divided into two groups: free-moving and following vehicles. In the mid-block bicycle lanes with mixed two-wheeled traffic, the headways of e-bikes, e-scooters and bicycles exhibit different distributional characteristics given distinct behaviors of cyclists. Accordingly, the headway distribution of two-wheeled vehicles is an aggregation of the headway distributions of e-bikes, e-scooters and bicycles. The headway distribution model for the mid-block bicycle lanes with mixed traffic flow is presented in the following sub-sections (Branston, 1976; Buckley,1968; Cowan, 1975; Hoogendoorn and Bovy, 1998; Hoogendoorn, 2005; Luttinen, 1996; Wasielewski, 1979).

2.1 Composite headway distribution model for vehicle type *p*

For vehicle type p, the probability density function of headways is given by:

$$f_p(t) = \phi_p u_p(t) + (1-\phi_p) v_p(t) \tag{1}$$

where $u_p(t)$ and $v_p(t)$ are the probability density functions of the constrained and unconstrained headways for vehicle type p; ϕ_p is the fraction of the constrained headways of vehicle type p. Let us define $u_{p1}(t)= \phi_p u_p(t)$ and $v_{p1}(t)=(1-\phi_p)v_p(t)$, f_p(t) is then given by:

$$f_p(t) = u_{p1}(t) + v_{p1}(t) \tag{2}$$

where $u_{p1}(t)$ is the probability density function of the constrained headways of vehicle type p scaled with the fraction of the constrained headways; and $v_{p1}(t)$ is the probability density function of the unconstrained headways of vehicle type p scaled with the fraction of the unconstrained headways.

Under low traffic-volume conditions, the two-wheeled vehicles in a bicycle lane are in free-moving states. The arrival of two-wheeled vehicles follows a Poisson process, and their headways are exponentially distributed. For sufficiently large headways t, $f_p(t)$ is given by:

$$f_p(t) = v_{p1}(t) = A_p \lambda_p \exp(-\lambda_p t) \quad for\, t > T_p \tag{3}$$

where T_p is a headway value beyond which the type p vehicles are in free-moving states; λ_p is the arrival rate for the type p free-moving vehicles; A_p is a normalization constant, which is determined on the basis of the observed headways of vehicle type p.

For headways $t < T_p$, the assumption about free moving is no longer valid, and the type p vehicles should be considered following vehicles. This correction for Eq.(3) is effectuated by removing from the exponential distribution the fraction of the type p vehicles that have preferred headways larger than t. The assumption is that no type p vehicles will be found at less than their preferred following headways (Buckley,1968; Hoogendoorn, 2005; Wasielewski, 1979). The fraction $\pi_p(t)$ of the type p following vehicles is given by:

$$\pi_p(t) = \int_t^{\infty} u_p(s)ds \tag{4}$$

where $u_p(s)$ is the probability density function of the constrained headways of the type p vehicles. For $t<T_p$, the $v_{p1}(t)$ is given by

$$v_{p1}(t) = A_p\lambda_p \exp(-\lambda_p t)\left[1-\pi_p(t)\right] = A_p\lambda_p \exp(-\lambda_p t)\left[1-\int_t^{\infty} u_p(s)ds\right] \qquad for\, t < T_p \qquad (5)$$
$$= A_p\lambda_p \exp(-\lambda_p t)\int_0^t u_p(s)ds$$

From Eq.(1), the following relationship can be obtained:

$$u_p(s)=\left[f_p(s)-v_{p1}(s)\right]/\phi_p \qquad (6)$$

where $f_p(s)$ is the probability density function for the headways of the type p vehicles; $v_{p1}(s)$ is the probability density function for the unconstrained headways of the type p vehicles scaled with the fraction of the unconstrained headways. Combing Eq. (5) and (6), the following integral equation for $v_{p1}(t)$ in terms of the observed distribution $f_p(t)$ and the parameters A_p and λ_p can be obtained:

$$v_{p1}(t) = \left(A_p\lambda_p/\phi_p\right)\exp(-\lambda_p t)\int_0^t\left[f_p(s)-v_{p1}(s)\right]ds \qquad for\, t < T_p \qquad (7)$$
$$=A_p\lambda_p \exp(-\lambda_p t)\left\{1\text{-}\left(1/\phi_p\right)\int_t^{\infty}\left[f_p(s)-v_{p1}(s)ds\right]\right\}$$

The parameters A_p and λ_p can be calculated based on the observed headways of the type p vehicles in the range $t>T_p$ with Eq.(3). Then the integral equation can be solved numerically being subject to the constraint

$$\phi_p = \int_0^{\infty} u_{p1}(s)ds \qquad (8)$$

to yield the quantity ϕ_p and the function $v_{p1}(t)$ in the range $t < T_p$. The $f_p(t)$ is given by:

$$f_p(t) = \phi_p u_p(t) + A_p\lambda_p \exp(-\lambda_p t)\left\{1\text{-}\left(1/\phi_p\right)\int_t^{\infty}[f_p(s)-v_{p1}(s)]ds\right\} \quad for\, t < T_p \qquad (9)$$

2.2 Composite headway distribution model for the overall two-wheeled vehicles

In a mid-block bicycle lane with mixed two-wheeled traffic the composite headway distribution for the overall two-wheeled vehicles is the aggregation of the headway distributions for e-bikes, e-scooters and bicycles. Let φ_p denote the proportion of vehicle type p in the mixed two-wheeled traffic, $\sum_p\varphi_p$=1. The probability density function $v_1(t)$ of the unconstrained headways of the overall two-wheeled vehicles can be approximately estimated with Eq.(10). The headway probability density function $f(t)$ of the overall two-wheeled vehicles can be approximately estimated with Eq.(11). The fraction ϕ of the constrained headways of the overall two-wheeled vehicles can be estimated with Eq.(12).

$$v_1(t)=\sum_{p=1}^{3}\varphi_p v_{p1}(t)=\begin{cases}\sum_{p=1}^{3}\varphi_p A_p\lambda_p \exp(-\lambda_p t)\left\{1\text{-}\left(1/\phi_p\right)\int_t^{\infty}\left[f_p(s)-v_{p1}(s)\right]ds\right\} & for\, t<T_p\\ \sum_{p=1}^{3}\varphi_p A_p\lambda_p \exp(-\lambda_p t) & for\, t>T_p\end{cases} \tag{10}$$

$$f(t)=\sum_{p=1}^{3}\varphi_p f_p(t)=\begin{cases}\sum_{p=1}^{3}\left\{\varphi_p\phi_p u_p(t)+\varphi_p A_p\lambda_p \exp(-\lambda_p t)\left\{1\text{-}\left(1/\phi_p\right)\int_t^{\infty}[f_p(s)-v_{p1}(s)]ds\right\}\right\} & for\, t<T_p\\ \sum_{p=1}^{3}\varphi_p A_p\lambda_p \exp(-\lambda_p t) & for\, t>T_p\end{cases} \tag{11}$$

$$\phi=\sum\nolimits_p \varphi_p\phi_p \tag{12}$$

2.3 Estimation of the composite headway distribution model

Previous studies have proposed numerous methods for estimating the parameters of the composite headway distribution models (Branston, 1976; Hoogendoorn and Botma, 1997; Luttinen, 1996; Wasielewski, 1979). The log-normal, gamma and beta distributions have been used to formulate the functional forms of the constrained headways (Branston, 1976; Hoogendoorn and Botma, 1997; Luttinen, 1996). The parameters of the composite headway distribution models were estimated based on the pre-specified functional forms of the constrained headways. Wasielewski proposed a distribution-free estimation procedure that does not need to specify the distributions of the constrained headways (Wasielewski, 1979). Compared with the conventional methods, the distribution-free estimation procedure reduces the number of the parameters of composite headway distribution models and simplifies the process of parameter estimation. The distribution-free estimation procedure was applied in this study to estimate the parameters in the composite headway distribution models, and to determine the probability density functions for the constrained headways.

2.3.1 Estimating the parameter T_p

When $t>T_p$, the type p vehicles are in free-moving states, and their headways follow the exponential distribution. However, with the presence of following vehicles, $t<T_p$, the assumption about exponential distribution does not hold true. The basic idea for determining T_p is that for $t > T_p$ there are no significant deviations from the exponential distribution, but for the interval between T_p-Δt and T_p there is a statistically significant deviation from the exponential distribution determined by the headways with $t > T_p$ (*19*). The detailed procedure for estimating T_p is given as follows.

The procedure starts from choosing T_{p0} as the upper limit value of T_p for the type p vehicles. The exponential distribution is determined by the observed headways that are greater than T_{p0}. To test a smaller value of T_p, the number of the headways in the interval between T_{p0}-Δt and T_{p0}, which is denoted by m_{p2}, is predicted with the exponential distribution. The predicted m_{p2} is then compared with the number of the observed headways of the type p vehicles in the interval Δt with a single-tailed test. The number m_{p2} is given by (Wasielewski, 1979)

$$m_{p2} = m_p \left[\exp(\lambda_p^{'} \Delta t) - 1 \right] \tag{13}$$

where m_p is the number of the headways larger than T_{p0}; m_{p1} is the number of the observed headways of the type p vehicles in the interval Δt; and λ'_p is the estimated value of the parameter λ_p. The variances of m_{p1} and m_{p2} are given by (Wasielewski, 1979)

$$\sigma^2(m_{p1}) = m_{p1} \left[1 - \left(m_{p1} / n_p \right) \right] \tag{14}$$

$$\sigma^2(m_{p2}) = \left(m_{p2}^2 / m_p \right) \left[1 - \left(m_p / n_p \right) \right] + \left[m_p \Delta t \exp(\lambda_p^{'} \Delta t) \right]^2 \sigma^2(\lambda_p^{'}) \tag{15}$$

where $\sigma^2(m_{p1})$ and $\sigma^2(m_{p2})$ are the variances of m_{p1} and m_{p2}; n_p is the total number of the observed headways of vehicle type p; $\sigma^2(\lambda'_p)$ is the variance of the estimated parameter λ'_p. With the assumption that $m_{p1}= m_{p2}$, the difference $\Delta m_p= m_{p1}- m_{p2}$ has a mean of zero and the variance of Δm_p is given by

$$\sigma^2(\Delta m_p) = \sigma^2(m_{p1}) + \sigma^2(m_{p2}) \tag{16}$$

where $\sigma^2(\Delta m_p)$ represents the variance of Δm_p. If the value $r_p=\Delta m_p/\sigma(\Delta m_p)$ is greater than 1.65, m_{p1} is significantly greater than m_{p2} at a 95% level of confidence, otherwise m_{p1} and m_{p2} are not significantly different. If the difference in m_{p1} and m_{p2} is not significant, $T_{p1}=T_{p0}-\Delta t$ is adopted, and a similar test is performed on the headways in the interval between $T_{p1}-\Delta t$ and T_{p1}. The process is repeated until m_{p1} is significantly greater than m_{p2} in the interval between $T_{pk}-\Delta t$ and T_{pk}. T_{pk} is then considered the estimated value of the parameter T_p.

2.3.2 Estimating the parameter λ_p

Based on the composite headway models, the number of free-moving vehicles whose headways are larger than T_p is exponentially distributed. The parameter λ_p can be estimated by maximizing the log-likelihood function of Eq.(5). The estimate λ'_p for λ_p is given by

$$\lambda'_p = \left[\left(1/m_p\right)\sum_i (t_{pi} - T_p)\right]^{-1} \tag{17}$$

where m_p is the number of the observed headways that are larger than T_p for the type p vehicles; and t_{pi} is the headway i for the type p vehicles, and t_{pi} is larger than T_p. The variance of λ_p is estimated by

$$\sigma^2(\lambda'_p) = \lambda'^2_p / m_p \tag{18}$$

where $\sigma^2(\lambda'_p)$ is the variance of the estimated parameter λ'_p.

2.3.3 Estimating the parameter A_p

The parameter A_p can be estimated by normalizing Eq.(3) on the basis of the observed number of headways that are greater than T_p:

$$A'_p = \left(m_p / n_p\right)\exp(\lambda'_p T_p) \tag{19}$$

where A'_p is the estimate of A_p; and n_p is the number of the observed headways for the type p vehicles.

2.3.4 Numeral solution of integral equation

Given the estimated parameters λ'_p, A'_p, and T_p, we can solve the following integral equation

$$v'_{p1}(t) = A'_p \lambda'_p \exp(-\lambda'_p t)\left\{1-\left(1/\phi'_p\right)\int_t^{\infty}[f'_p(s)-v'_{p1}(s)]ds\right\} \tag{20}$$

subject to the condition

$$\phi'_p = \int_0^{\infty}[f'_p(s)-v'_{p1}(s)]ds \tag{21}$$

where $v'_{p1}(t)$ is the estimate of the probability density function of the unconstrained headways of the type p vehicles scaled with the fraction of the unconstrained headways; $v'_{p1}(s)$ is an alternative expression of $v'_{p1}(t)$ in the integral equation; $f'_p(s)$ is the estimate of the probability density function of the headways of vehicle type p; and ϕ'_p is the estimate of the fraction of the constrained headways of the type p vehicles. The integral equation can be solved with an iterative approach. The k^{th} approximation of $v'_{p1}(t)$ can be calculated from the $(k-1)^{th}$ approximation, which is given as follows:

$$v'^{(k)}_{p1}(t) = A'_p \lambda'_p \exp(-\lambda'_p t)\left\{1-\left(1/\phi'^{(k-1)}_p\right)\int_t^{\infty}[f'_p(s)-v'^{(k-1)}_{p1}(s)]ds\right\} \tag{22}$$

The iteration is repeated until the error $|v'^{(k)}_{p1}(t)-v'^{(k-1)}_{p1}(t)|$ meets the convergence criterion. The initial iteration is given by $v'^{(0)}_{p1}(t)=A'_p\lambda'_p exp(-\lambda'_p t)$ and $\phi'^{(0)}_p=0.9$. The probability density function of the constrained headways of the type p vehicles can be estimated by

$$u'_{p1}(t) = \phi'_p u'_p(t) = f'_p(t) - v'_{p1}(t) \tag{23}$$

where $u'_{p1}(t)$ is the estimate of the probability density function of the constrained headways of the type p vehicles scaled with the fraction of the constrained headways; and $u'_p(t)$ is the estimate of the probability density function of the constrained headways of the type p vehicles. The probability density function of the constrained headways of the overall vehicles in the mixed traffic flow is given by

$$u'(t) = \sum_p\left[\varphi_p u'_{p1}(t)/\phi'_p\right] = \sum_p\left(\varphi_p/\phi'_p\right)[f'_p(t)-v'_{p1}(t)] \tag{24}$$

where $u'(t)$ is the constrained headways of the overall vehicles in the mixed traffic flow.

3. DATA COLLECTION

Data were collected at five mid-block bicycle lanes in Nanjing, China. Figure 2 depicts the typical layout of a mid-block bicycle lane in urban areas in China. Most of the bicycle lanes in China are unidirectional and are deployed on both sides of urban streets. Physical barriers or medians are used to separate bicycles lanes from motorized lanes and pedestrian lanes. In the present study, the mid-block bicycle lanes were defined as a length of the bicycle lanes between two neighboring signalized intersections. The widths of the selected bicycle lanes were 3.0, 3.2, and 3.5 m, respectively, allowing two cyclists to ride side by side, or three cyclists to stop side by side. All the selected mid-block bicycle lanes had similar pavement conditions. In addition, there was no on-street parking space and bus stops.

A video camera was setup in the field to record traffic data. Data were recorded during weekday peak periods from 6:30-8:30 in the morning and 5:30-7:30 in the afternoon under fair weather conditions. The recorded videos were reviewed in the laboratory for data reduction. By reviewing the collected videos, the following information was obtained: (a) the headways of two-wheeled vehicles; (b) the operating speeds of two-wheeled vehicles; and (c) the type of two-wheeled vehicles. VideoStudio was used to process the recorded video in a frame-by-frame way at a rate of 25 frames per second such that the researchers could record the arrival time of different vehicles accurately, and capture the slight difference among the headways of different types of two-wheeled vehicles. The operating speeds of the two-wheeled vehicles were estimated by measuring the distance between two pre-specified reference lines in the video, and the elapsed time spent by each vehicle passing the reference lines in the video.

In total, 17,166 two-wheeled vehicles, including 4,895 e-bikes, 5,739 e-scooters and 6,532 bicycles, were observed at the selected sites. The characteristics of selected sites and the statistical description of field data were given in Table 1, including the width of each bicycle lane, the height of the physical barriers, the number of two-wheeled vehicles, the proportions of e-bikes and e-scooters, the average headways, the average speeds and the flow rates of two-wheeled vehicles.

In this study, the headway of a two-wheeled vehicle was measured as the difference in the passage times of the leading and the following two-wheeled vehicles in mid-block bicycle lanes. Because cyclists may ride side by side in bicycle lanes, both leading and following vehicles need to be clearly identified for defining a particular headway. Let h_{pi} denote the time at which vehicle i of type p arrives at a reference line. Let $y_{pi}(h_{pi})$ denote the lateral position of the vehicle i of type p at h_{pi}, which was indicated by the crossing marks in Figure 3. The lateral position measures the distance from the crossing mark to the barrier between the motorized and bicycle lanes. For a particular headway, the following relationship between the leading and following vehicles needs to be satisfied:

$$\left| y_{pi}(h_{pi}) - y_j(h_j) \right| \leq W_p \tag{25}$$

where W_p represents the width of the handlebars of the type p vehicles plus the additional distances on both sides; h_j is the time at which the leading vehicle j arrives at the reference line; $y_j(h_j)$ denotes the lateral position of type p vehicle i at h_j. The parameter W_p was set to be 0.8, 0.8 and 0.7 m for e-bikes, e-scooters and bicycles, respectively. The detailed description of the headway definition was given in Figure 3. In Figure 3, W_{AD}, W_{BD}, and W_{CD} are all smaller than W_p, indicating that vehicle D is impeded by vehicle A, B and C from different directions, simultaneously. However, vehicle B is the nearest vehicle that impedes vehicle D. Thus, in this condition we consider that vehicle D is following vehicle B. The headway t_{pi} of type p vehicle i is then defined as:

$$t_{pi} = h_{pi} - h_j \tag{26}$$

In the present study the headways were defined based on the following vehicle, and accordingly, three types of headways were considered: the headways of e-bikes, e-scooters and bicycles. The definition of the headways is consistent with those used in previous studies (Branston, 1976; Buckley, 1968; Cowan, 1975; Hoogendoorn and Botma, 1997; Hoogendoorn and Bovy, 1998; Hoogendoorn, 2005; Hoogendoorn and Daamen, 2016; Luttinen, 1996; Wasielewski, 1979).

4. RESULTS OF COMPOSITE HEADWAY DISTRIBUTION MODELS

Previous studies have suggested that when the headway was greater than 4.0 s bicycles were in free-moving states (Hoogendoorn and Daamen, 2016). In the present study, we chose 4.0 s as the upper limit for estimating T_p. The distributions of the observed headways of e-bikes, e-scooters and bicycles were compared with the exponential distributions. The process of determining T_p at the selected sites was given in Table 2. For e-bikes and e-scooters, the differences in the observed headways and exponential distributions were statistically significant in the time interval between 1.5 and 2.0 s, but not significant in the time interval between 2.0 and 2.5 s. For bicycles, the differences in the observed headways and exponential distributions were statistically significant in the time interval between 2.5 and 3.0 s, but not significant in the time interval between 3.0 and 3.5 s. Therefore, T_p was set as 2.0 s for e-bikes and e-scooters, and 3.0 s for bicycles. Based on the estimated T_p, the parameters λ_p, A_p and ϕ_p were then estimated for each of the selected sites. The results were given in Table 3.

5. HEADWAYS

The iterative approach was used to estimate the probability density functions of the constrained and unconstrained headways of two-wheeled vehicles. The effects of the proportions of e-bikes, e-scooters and bicycles on the distributions of different kinds of headways were identified in this section.

5.1 Distributions of headways

The headways smaller than T_p were evenly divided into ten intervals from 0 to 2.0 s for e-bikes and e-scooters, and fifteen intervals from 0 to 3.0 s for bicycles. Given the parameters λ'_p, A'_p, and ϕ'_p in Table 3, the probability density functions $v'_{p1}(t)$ of the unconstrained headways of e-bikes, e-scooters and bicycles were estimated with Eq.(20) and (22). Following the iterative approach discussed before, the Eq.(22) reached convergence in fourteen steps, and the error $|v'^{(k)}_{p1}(t)-v'^{(k-1)}_{p1}(t)|$ was less than 10^{-6}. Given $v'_{p1}(t)$ and ϕ'_p, the probability density functions of the constrained headways of different two-wheeled vehicles were estimated with Eq.(23) and (24). The probability density function of the unconstrained headways of the overall two-wheeled vehicles was estimated with Eq.(10). Using data collected from site 5, Figure 4 and 5 were developed as examples to illustrate the headway distributions of two-wheeled vehicles. Figure 4 depicts the probability distributions of the constrained headways for the overall two-wheeled vehicles, e-bikes, e-scooters and bicycles, while Figure 5 depicts the headway distributions of the overall two-wheeled vehicles, e-bikes, e-scooters and bicycles.

In Figure 5, $f_{hist}(t)$ represents the probability density function for the empirical headway distribution of the overall two-wheeled vehicles, and $f_{phist}(t)$ represents the probability density function for the empirical headway distribution of e-bikes, e-scooters and bicycles. Figure 6 depicts the conditional probability of the constrained headways for different types of two-wheeled vehicles. The conditional probability of the constrained headways was defined as the estimated distribution of the constrained headways scaled with the estimated fraction of the constrained headways divided by the empirical headway distribution, or in other words, $\theta(t) = u'_{p1}(t)/f_{phist}(t)$. As shown in Figure 6, the conditional probability of the constrained headways for e-bikes, e-scooters and bicycles decreased with an increase in the headways, indicating that there are more constrained headways in the mixed two-wheeled traffic flow under heavy traffic conditions than those under light traffic conditions.

5.2 Effects of the proportions of e-bikes, e-scooters and bicycles

The proportions of e-bikes, e-scooters and bicycles may affect the headway distributions of two-wheeled vehicles. Figure 7 depicts the effects of the proportions of e-bikes, e-scooters and bicycles on the distributions of unconstrained and constrained headways of two-wheeled vehicles at site 5. If the proportion of bicycles was fixed, the proportions of e-bikes and e-scooters had minor effects on both unconstrained and constrained headways of overall two-wheeled vehicles at all selected sites. Given that the proportion of e-bikes/e-scooters was fixed, with the increase in the proportions of e-scooters/e-bikes the probability of unconstrained headways that were relatively small (<10 s) may slightly increase, the probability of the constrained headways that were smaller than 1.0 s may greatly increase, and the probability of the constrained headways that were larger than 1.0 s may decrease.

6. CAPACITY OF MID-BLOCK BICYCLE LANES

In the present study, a procedure based on the estimated composite headway distribution models was proposed for estimating the capacity of a mid-block bicycle lane. Capacity was defined as the maximum number of two-wheeled vehicles that can pass a given point during a specified period under prevailing roadway, traffic, and control conditions (HCM, 2010). The minimum headways varied across different types of two-wheeled vehicles, and accordingly, the capacity can be calculated by the reciprocal of the mean of the minimum headways of overall two-wheeled vehicles. Previous studies have suggested that the constrained headways of two-wheeled vehicles were minimum headways under saturated conditions. Accordingly, the capacity can be estimated as the reciprocal of the expectation of the probability density function of constrained headways of overall two-wheeled vehicles (Hoogendoorn and Botma, 1997; Hoogendoorn and Bovy, 1998; Hoogendoorn, 2005; Hoogendoorn and Daamen, 2016).

6.1 Capacity estimation method

With this assumption and definition, the fraction of the constrained vehicles equaled 1 for all vehicle types. For vehicle type p, the headway probability density function is given by

$$f_p(t)\Big|_{\phi'_p=1} = u_p(t) \tag{27}$$

where $f_p(t)|_{\phi'_p=1}$ is the headway probability density function of type p vehicles. The expectation of $f_p(t)|_{\phi'_p=1}$ is then given by

$$E_p(t)\Big|_{\phi'_p=1} = \int_0^{T_p} tu_p(t)dt \tag{28}$$

where $E_p(t)|_{\phi'_p=1}$ is the expectation of $f_p(t)|_{\phi'_p=1}$. The capacity of the mid-block bicycle lanes for type p vehicles can be estimated by

$$C_p = 3600 / E_p(t)\Big|_{\phi'_p=1} = 3600 / \int_0^{T_p} tu_p(t)dt \tag{29}$$

where C_p is the capacity of a mid-block bicycle lane for vehicle type p (bicycle/h).

In a mid-block bicycle lane with mixed two-wheeled traffic, the headway probability density function of the overall two-wheeled vehicles is the aggregation of the headway probability density functions of e-bikes, e-scooters and bicycles, considering the proportions of different two-wheeled vehicles. The headway probability density function of the overall two-wheeled vehicles is given by

$$f(t)\Big|_{\phi'_p=1} = \sum_{p=1}^{3} \varphi_p f_p(t)\Big|_{\phi'_p=1} = \sum_{p=1}^{3} \varphi_p u_p(t) \tag{30}$$

where $f(t)|_{\phi'_p=1}$ is the headway probability density function of the overall two-wheeled vehicles in the condition that all the two-wheeled vehicles are in following states. The expectation of $f(t)|_{\phi'_p=1}$ is given by

$$E(t)\Big|_{\phi'_p=1} = \sum_{p=1}^{3} \varphi_p E_p(t)\Big|_{\phi'_p=1} = \sum_{p=1}^{3} \varphi_p \int_0^{T_p} tu_p(t)dt \tag{31}$$

where $E(t)|_{\phi'_p=1}$ is the expectation of $f(t)|_{\phi'_p=1}$.

The capacity of the mid-block bicycle lanes for the overall two-wheeled vehicles can be estimated by

$$C = 3600 / E(t)\Big|_{\phi'_p=1} = 3600 / \sum_{p=1}^{3} \varphi_p \int_0^{T_p} tu_p(t)dt \tag{32}$$

where C is the capacity of a mid-block bicycle lane for the overall two-wheeled vehicles (bicycle/h). With the estimated capacity of e-bikes, e-scooters and bicycles, the bicycle equivalent factors for e-bikes and e-scooters with respect to bicycles can be determined with Eq.(33) and (34).

$$BEF_{e-bike} = C_{bicycle} / C_{e-bike} \tag{33}$$

$$BEF_{e-scooter} = C_{bicycle} / C_{e-scooter} \tag{34}$$

where $BEF_{e\text{-}bike}$ and $BEF_{e\text{-}scooter}$ are the bicycle equivalent factors for e-bikes and e-scooters with respect to bicycles, respectively; $C_{e\text{-}bike}$, $C_{e\text{-}scooter}$ and $C_{bicycle}$ are the capacity of a mid-block bicycle lane for the e-bikes, e-scooters and bicycles, respectively (bicycle/h).

6.2 Results of capacity estimation

The collected data were evenly divided into forty groups based on 0.5-h time intervals. Based on the field data at selected sites, the capacity of the overall two-wheeled vehicles, e-bikes, e-scooters and bicycles for different 0.5-h time intervals at all the selected sites were estimated, and the results were given in Table 4.

Linear regression models were conducted to identify if the relationship between the estimated capacity and the widths of mid-block bicycle lanes was statistically significant. The results suggested that the widths of mid-block bicycle lanes did not significantly affect the capacity of different kinds of two-wheeled vehicles ($p_{overall}$= 0.209, $p_{e\text{-}bike}$=0.360, $p_{e\text{-}scooter}$=0.470, $p_{bicycle}$=0.326). Note that the finding may only apply to the selected sites, at which the width of bicycle lanes was from 3.0 to 3.5 m.

Linear regression models were also conducted to identify if the relationship between the estimated capacity and the proportions of e-bikes, e-scooters and bicycles was statistically significant. The results indicated that there were significant positive correlations between the capacity and the proportions of e-bikes and e-scooters ($\text{coefficient}_{\text{e-bike}}$ = 0.499, $p_{e\text{-}bike}$=0.001; $\text{coefficient}_{\text{e-scooter}}$ = 0.537, $p_{e\text{-}scooter}$<0.001), while there were significant negative correlation between the capacity and the proportion of bicycles (coefficient$_{bicycle}$ = -0.829, $p_{bicycle}$<0.001). The finding suggested that the increase in the proportions of e-bikes and e-scooters increased the capacity of a mid-block bicycle lane for the overall two-wheeled vehicles.

Because the width of mid-block bicycle lanes did not significantly affect the capacity for two-wheeled vehicles, the data at all the selected sites were aggregated to estimate the capacity for overall two-wheeled vehicles, e-bikes, e-scooters and bicycles. The estimated capacity of a mid-block bicycle lane for e-bikes, e-scooters and bicycles was 3,757, 3,804 and 2,791 bicycles/h, respectively, and the aggregated capacity of a mid-block bicycle lane was 3,332 bicycles/h. The bicycle equivalent factor for e-bikes and e-scooters with respect to bicycles was 0.7429 and 0.7337, respectively.

With the composite headway distribution model models, curves can be developed to help decision makers estimate the capacity of a mid-block bicycle lane given the proportions of different types of two-wheeled vehicles, and the curves were depicted in Figure 8. For example, the capacity of a mid-block bicycle lane was 3,419 bicycles/h given that the proportions of e-bikes and e-scooters in two-wheeled traffic were 30% and 40%, respectively (see Figure 8).

6.3 Validation of the proposed capacity estimation method

The proposed capacity estimation method was validated using the data collected from two mid-block bicycle lanes that were not used for capacity estimation. The validation data set includes eight hours data, which covers 6,458 two-wheeled vehicles, including 1,640 e-bikes, 3,084 e-scooters and 1,734 bicycles. The validation data were evenly divided into sixteen groups based on 0.5-h time intervals. In each time interval, the data were further divided into thirty groups based on 1-min time intervals. In each 1-min time interval the flow rate of two-wheeled vehicles was measured, and the capacity of a bicycle lane was estimated as the maximum flow rate of two-wheeled vehicles in each 0.5-h time interval. Note that all the data were collected during peak periods and the flow rate of two-wheeled vehicles at the selected sites was high. Thus, the field measured maximum flow rate can be considered reasonably close to capacity.

Two statistics were used for validating the proposed capacity estimation method: the mean absolute deviation (MAD) and the mean absolute percent error (MAPE). The definitions of MAD and MAPE are given by

$$\text{MAD}=(1/K)\sum_{k=1}^{K}\left|C_k - C_{mk}\right| \tag{35}$$

$$\text{MAPE}=(1/K)\sum_{k=1}^{K}\left|(C_k - C_{mk})/C_{mk}\right| \tag{36}$$

where C_k is the estimated capacity in the k^{th} 0.5-h time interval (bicycle/h), C_{mk} is the capacity measured in the k^{th} 0.5-h time interval (bicycle/h), and K represents the number of time intervals. The validation results were given in Table 5. The MAD value varies from 5 to 105 bicycles/h with a mean of 55 bicycles/h, and the MAPE value varies from 0.14% to 3.12% with a mean of 1.63%. The validation results indicate the proposed capacity estimation method provides reasonable estimates for the capacity of mid-block bicycle lanes for overall two-wheeled vehicles.

The estimated and field measured capacity of mid-block bicycle lanes considering different proportions of e-bikes, e-scooters and bicycles were depicted in Figure 9. The x-axis represents the proportion of e-bikes and e-scooters, and the y-axis represents capacity. Two lines were developed: the solid line which was fitted by the field measured capacity, and the dashed line which was fitted by the estimated capacity. As shown in Figure 9, the field measured capacity data were randomly distributed around the dashed line, and the dashed line almost coincided with the solid line. The results indicated that the proposed capacity estimation method provided generally unbiased estimates for the capacity of mid-block bicycle lanes.

7. SUMMARY AND DISCUSSIONS

This study proposed a procedure for estimating the capacity of mid-block bicycle lanes with mixed two-wheeled vehicles. Composite headway distribution models were developed to identify the headway distributions of e-bikes, e-scooters and bicycles. A distribution-free estimation approach was followed to determine the key parameters of the composite headway distribution models. With the estimated composite headway distribution models, a procedure was proposed for estimating the capacity of mid-block bicycle lanes with mixed two-wheeled traffic. The proposed capacity estimation method was validated against field data, and the results suggested that the proposed method provides reasonable estimates for the aggregated capacity of mid-block bicycle lanes.

The proportions of e-bikes and e-scooters significantly affected the headway distribution of overall two-wheeled vehicles and the capacity of mid-block bicycle lanes for overall two-wheeled vehicles. The constrained headways of overall two-wheeled vehicles may decrease as the proportions of e-bikes and e-scooters increase. Accordingly, the capacity of mid-block bicycle lanes for overall two-wheeled vehicles may increase as the proportions of e-bikes and e-scooters increase.

There are two limitations in the present study which should be addressed in future work. In the present study, the widths of the selected mid-block bicycle lanes were from 3.0 to 3.5 m, and all the selected mid-block bicycle lanes allow two cyclists to ride side by side. It may be one of the possible reasons that the width did not significantly affect the capacity of mid-block bicycle lanes for overall two-wheeled vehicles. Future study should be focus on the influences of various widths on the capacity of mid-block bicycle lanes. In addition, we did not consider the influences of leading vehicles on the headways of e-bikes, e-scooters and bicycles. For example, the differences of the headways of e-bikes that are following e-bikes, e-scooters and bicycles were not considered in this study. More research is needed to investigate the influences of different leading vehicles on the headways of e-bikes, e-scooters and bicycles, respectively.

The capacity estimation results can be directly applied to the mid-block bicycle lanes with similar widths and layouts. However, the capacity estimations results may not be appropriate for the bicycle lanes with heterogeneous conditions. In this condition, the proposed capacity estimation method can be directly used for estimating the capacity of mid-block bicycle lanes, given the geometric design characteristics and traffic conditions.

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