An Improved Follower Recognition Procedure to Estimate Follower Flow-Based Quality of Service Measures

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Abstract: For a follower-based service measure to be effectively used for two-lane highway quality of service evaluation, a more reliable follower identification procedure is necessary. Current follower recognition methodologies are based on single critical headway values that may not accurately identify followers since they do not take into account the randomness of preferred tracking headways and drivers' desired speeds. This paper presents an improved, probability-based follower identification methodology that takes both of these factors into account while also considering their variability across different driving conditions. The calculated follower percentage and follower density values were compared with those estimated using the 3-second threshold suggested by the HCM. The proposed methodology estimated more followers, particularly during periods of heavy flow, highlighting the inability of using a single headway value to correctly identify followers. The resulting follower counts have been normalized, making it possible to theoretically identify followers at any given time or driving condition.

Key Words: *two-lane highways, quality of service, follower flow*

1. INTRODUCTION

To determine whether a vehicle is in a following state, the current practice is to simply compare its headway with a pre-defined critical headway value, such as the 3-second threshold suggested by the Highway Capacity Manual (HCM). This is a simplification of the follower identification process for practicality and for convenience in field measurement. This however has obvious drawbacks since assigning a single headway value to classify followers assumes that all vehicles behave exactly the same way under different conditions (i.e., traffic, geometric, weather, etc.) and does not take into account the randomness of driver behavior. In other studies, different critical headways (e.g. 3.5-seconds, 4-seconds, etc.) are used depending on the findings of the researchers.

With previous studies identifying *follower density* as the most suitable service measure for two-lane highway facilities (Van As, 2004; Catbagan and Nakamura, 2006), a more reliable follower recognition procedure is necessary to accurately evaluate service levels of two-lane highway operations. Using headway alone as a basis for follower identification is insufficient. Some drivers who may seem to be following due to low headways may actually be content with their current driving speed, which means that they are in fact, free vehicles. Conversely, some drivers who choose to drive more carefully may opt to follow their respective immediate lead vehicles in headways greater than the single-value threshold, thus falsely identifying them as non-following. Having a single critical headway value as a criterion is therefore an inadequate way to distinguish following and free vehicles, and speed should be given equal

consideration.

1.1 Objectives and Scope

With the nature of a following vehicle established, it thus becomes necessary to develop a follower recognition procedure, which does not only consider both headway and speed, but also takes into account driver behavior under various driving conditions. The main goal of this study is to establish a more reliable follower identification methodology, which can then be later used for analyzing follower flow in any given two-lane highway section. Determining the number of followers at any given time period can thus provide useful insight on how the highway is performing in terms of service quality. Another objective of this research initiative is to propose a more general definition of a following vehicle as well as an evaluation of how the proposed methodology compares with existing procedures, particularly the use of the HCM 3-second threshold.

However, since the data used for the development of the models in this study were taken from a typical two-lane highway in Japan, where passing is not allowed, the developed procedures can only be applied to similar facilities.

1.2 Related Literature

Issues about the use of single critical headway values for follower recognition has been raised in a number of vehicle bunching studies, since the criteria to classify vehicles in a platoon significantly varies across different studies (Taylor *et al.*, 1974). This was further reinforced by research suggesting that followers, observed in real-life traffic (unconstrained) operations, could also take rather large headways (Botma *et al.*, 1980; Hoogendoorn and Botma, 1997).

As earlier mentioned, the 3-second critical headway is suggested threshold by the HCM to identify whether a vehicle is following or not (HCM, 2000). This does not consider the random nature of driver preferences and simply assumes that all road users behave the same way in any driving condition. Follower density, defined as the number of followers per kilometer per lane, is being used as the service measure for two-lane highways in South Africa. However, this measure is still determined by a single-value, critical headway (Van As, 2004). The same service measure has been proposed by Catbagan and Nakamura to be used in evaluating quality of service (QOS) of Japan two-lane highways (Catbagan and Nakamura, 2006), but they also recommended to develop a more logical and realistic method of identifying followers (Catbagan and Nakamura, 2008).

Numerous studies have been made concerning the development of headway distribution models mainly for investigating arrival patterns and estimating capacities. Of particular concern for this research however are the studies conducted on composite (or mixed) headway distribution models, which aim to logically segregate the following and non-following components of the total headway distribution. This procedure is a significant step into properly identifying followers while taking the randomness of drivers' preferences into consideration at the same time.

A mixed distribution model introduced by Buckley (1968) provides a means to calculate both the constrained and unconstrained elements of the total distribution, and is widely known as the Semi-Poisson Model (SPM). He stated in his paper describing the development of this model that, in single-lane traffic, the only inhibition to the underlying Poisson process is the existence of the zone of emptiness, which has a probability density function given by $g(t)$. The

zone of emptiness, or more commonly called the 'empty zone', is the time headway maintained by a constrained driver, which may also be referred to as the *preferred following* (or *tracking*) *headway* in subsequent discussions.

Among the more well-known composite headway distribution models are those proposed by Cowan, which formulated four different headway models of increasing complexity. His last two models, aptly named M3 and M4, present a simplified and a more generalized representation of following and free vehicle headway distributions, respectively (Cowan, 1975).

Another model introduced by Branston (1976), more commonly known as Branston's Generalized Queuing (BGQ) model, also distinguishes following and free-flowing vehicles. Its main difference with the SPM is that Buckley's model obtains non-following headways by comparing an exponential headway with a following headway, while the BGQ obtains constrained headways by adding an exponential gap to the following headway. Luttinen (1996) however argued that both models are virtually the same.

1.3 Data Collection Site

The analysis of following behavior necessitates the collection of headway information, thus the need for individual vehicle data (or raw pulse data) was established. For this purpose, a laboratory-commissioned detector was set-up at a strategically selected observation point in Kiso, Nagano. The detector was installed at KP119.9 of Route 19, a slightly sloping two-lane highway section where passing is restricted. The relative distance of the vehicle sensor to the nearest major signalized intersections are 1.6-km and 2.6-km to the north and south of the detector, respectively. It is also important to note that the detector is located on a grade transition segment of about 3.66% to 4.44% upgrade in the northbound (NB) direction.

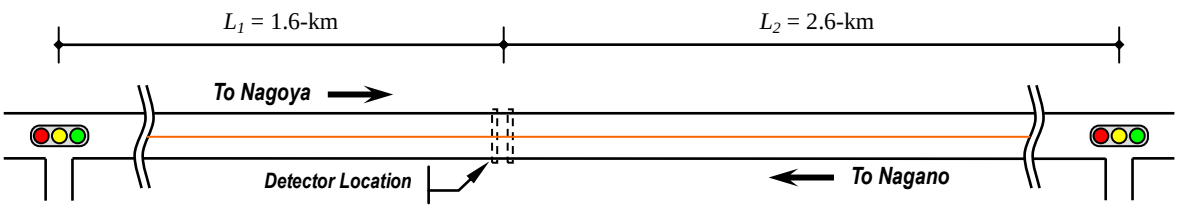


Figure 1 Schematic layout of detector location in the study area

Some preliminary analyses have been conducted in the same section and some of the findings have been incorporated in this study. The detected lengths were calibrated so that vehicles can be classified according to different vehicle types (Catbagan and Nakamura, 2007), but for the purpose of this study, vehicle classification will be limited to passenger cars (PC) and heavy vehicles (HV). The same condition for vehicle type recognition was used in another previous study about two-lane highway desired speed distributions (Taylor *et al.*, 1974).

2. FOLLOWER IDENTIFICATION METHODOLOGY

A more general definition of '*following*' is traveling below the driver's desired speed due to the presence of a relatively slower lead vehicle. A 'follower' can therefore be defined as *a vehicle traveling below its driver's desired speed at the driver's preferred following headway*.

This takes into account users' perception of service level since it can be safely assumed that the time spent traveling at a reduced speed (i.e. less than the desired speed) is directly related to driver dissatisfaction.

The stochastic nature of road users' preferences has been mentioned earlier and is true across different drivers. Preferred tracking headways and desired speeds can vary within any given driver, traveling under different driving conditions, further emphasizing its randomness. With the imposition of the simultaneous occurrence of traveling at the preferred tracking headway and below the desired speed to determine a following vehicle, it becomes necessary to develop a procedure that can identify a follower given these conditions.

A key objective of this research is to find a way to integrate both headway and speed into the following identification methodology while considering the major influencing factors affecting follower flow. This is done while simultaneously taking into account the variability of tracking headway and speed preferences among drivers and within each driver themselves when traveling at different driving conditions.

2.1 Headway-based Following Probability

In theory, the probability that a vehicle is in a following state increases as it goes closer to its immediate leader. In other words, the following probability of a vehicle based on headway alone decreases as the headway increases. If we hypothesize that the ratio of followers to free vehicles also decrease as headway increases and that a maximum critical headway t_{crit} exists (i.e. vehicles can no longer be considered in a state of following with headways greater than this value), then a theoretical headway-based following probability function $P(Foll_{headway})$ can be drawn and is shown in Figure 2. Based on the given hypothesis, the rate of decrease of following probability increases with headway, giving the theoretical shape of the conditional probability function, $P(Foll_{headway})$.

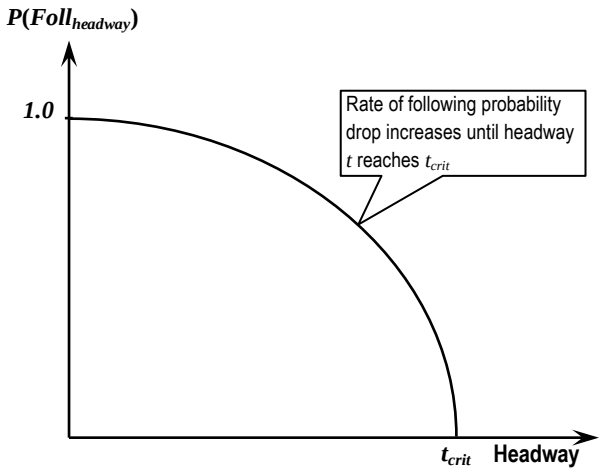


Figure 2 Theoretical representations of following probability based on headway

The composite headway distribution model developed by Buckley was earlier mentioned in the review of related research. This model, widely known as the Semi-Poisson Model, will be used in this study as the basis for decomposing the collected headways into either constrained or unconstrained. The general form of this model is given by the following probability density function $f(t)$:

$$f(t) = \phi g(t) + (1-\phi)h(t) \tag{1}$$

where $g(t)$ and $h(t)$ are the constrained and unconstrained components, respectively, and ϕ is the proportion of the constrained vehicles. At $\phi = 0$, or the absence of following vehicles, all vehicles would belong to the unconstrained group, which can be appropriately represented by an exponential function corresponding to random arrival times. The theoretical form of the composite headway distribution model and its corresponding components is illustrated in Figure 3.

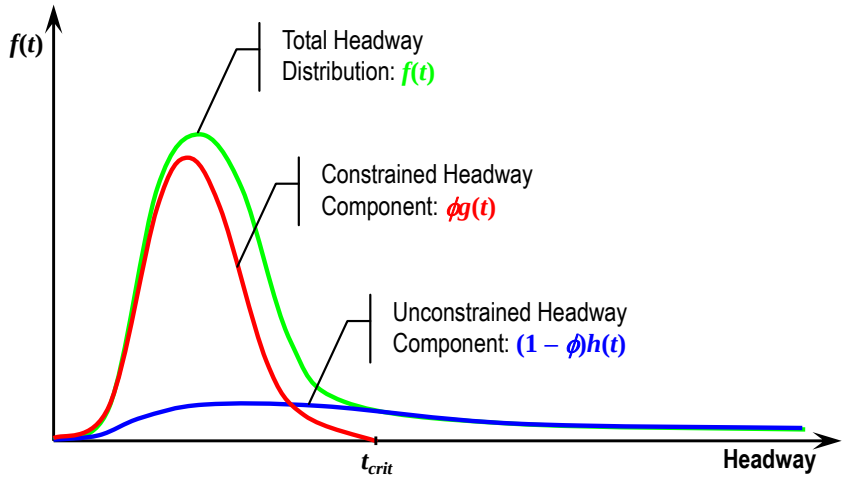


Figure 3 Theoretical form of the composite headway distribution model

For small values of t, g-type (constrained) headways predominate since most cars are in a following state, while for larger t, the influence of the h-type (unconstrained) headways increases until these swamp the constrained headways. Note that in Figure 3, the upper limit of the following distribution component is t_{crit}, or the maximum headway which followers still theoretically exist.

The non-parametric, distribution-free approach proposed by Wasielewski (1974) was used to reformulate the Semi-Poisson model into an integral equation wherein the components can be directly calculated from the observed headway distribution. The original model was rewritten to define components $g_1(t) = \phi g(t)$ and $h_1(t) = (1 - \phi)h(t)$, such that

$$f(t) = g_1(t) + h_1(t) \tag{2}$$

Once $h_1(t)$ is estimated using the non-parametric, distribution-free approach, the details of which are described in a number of publications (Catbagan and Nakamura, 2008; Wasielewski, 1974; Hoogendoorn, 2005; Catbagan, 2008), $g_1(t)$ can then be easily solved using Equation (2) ($f(t)$ and $h_1(t)$ are known). Since all the components of the composite headway model have been established, the headway-based following probability function can now be estimated by calculating the ratio of following vehicles to non-following vehicles based on the composite model. This conditional probability function, henceforth denoted as $\theta(t)$, is given by the equation

$$\theta(t) = \frac{g_1(t)}{f(t)} = P(Foll_{headway}) \tag{3}$$

where $g_1(t)$ is the constrained headway distribution function, $f(t)$ the distribution of observed headways and $P(Foll_{headway})$ the probability that a vehicle is following given its headway alone. This function (θ) is also used in the estimation of desired speed distributions, which will be discussed in the succeeding sections.

2.2 Speed-based Following Probability

The other component for follower recognition is speed, or more specifically, desired speed. Similar to preferred tracking headways, this varies across different drivers making it difficult to assess whether an observed vehicle, with a relatively short headway, is following or not. In fact, the desired speed of any given driver can change at any given time while driving, depending on the constantly changing environment around the vehicle while it is traveling. This phenomenon however is still much too complex to study at this time, given the current technological limitations in data collection. In this research, it is assumed that each driver has a corresponding desired speed while traveling at a given driving condition and that desired speed shall remain constant unless the driving condition changes. This assumption also means that the desired speeds are actually the maximum speeds of vehicles. If a vehicle's speed falls below its driver's desired speed, assuming no other external factors are being applied, then it is most likely to be following a slower vehicle. To estimate this likelihood, it is therefore necessary to make a procedure to determine the probability of a vehicle being in a following state given only its speed.

Suppose the desired speeds of various drivers are assumed to follow a certain distribution $f_d(v)$, then based on the premise that followers are traveling below their preferred free speeds it can be said that the probability of a vehicle traveling freely (i.e. not following), based on a given speed v_i alone, can be expressed as:

$$P(Free \mid v_i) = \int_0^{v_i} f_d(v)dv \tag{4}$$

Given this function, it therefore follows that the probability of a driver, traveling at speed v_i, is traveling below his desired speed (or the vehicle's following probability based on speed alone) is simply, $1 - P(Free| v_i)$ or

$$P(Foll \mid v_i) = 1 - \int_0^{v_i} f_d(v)dv = \int_{v_i}^{\infty} f_d(v)dv \tag{5}$$

This is better explained graphically in Figure 4, where it shows that if the speed v_i of an observed vehicle i was detected, the probability that the driver's desired speed is greater than his actual speed v_i, is represented by the shaded region of the function $f_d(v)$.

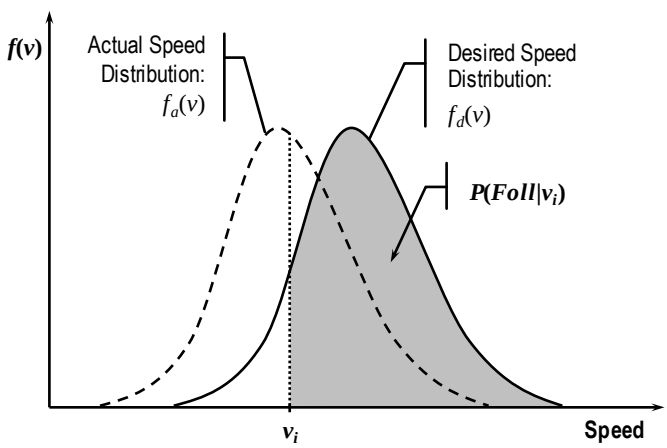


Figure 4 Theoretical representation of following probability based on speed

To estimate desired speeds, the unified free speed distribution method developed by Hoogendoorn (2005) was used. The same procedure was utilized in a previous study about variations of desired speed distributions in Japan two-lane highways (Catbagan and

Nakamura, 2008). It is important to note that in this study, free speed distributions are assumed to be equivalent to desired speed distributions. Of course this is only true for ideal geometric conditions, such as having a relatively flat gradient. Steep upgrades could physically limit the speed of vehicles even though desired speeds have yet to be achieved, which invalidates the equivalency of the two distributions. This is one of the major reasons why the data from the upgrade lane of the study section have been excluded from the analysis, pending additional data taken from different sites with varying grade conditions.

The survival function of the desired speed distribution estimate, which is a generalization of the original distribution-free method of Kaplan and Meier (1958) that includes partially censored observations, is given by

$$S_{\infty}(v^0) = \prod_{j=1}^{n_{v^0}} \left(\frac{n-j-1}{n-j-\theta_j} \right) \tag{6}$$

where n_{v^0} is the number of samples of v_i that are smaller than or equal to v0 (i.e. $v_j \leq v^0$, j = 1, . . . ,), n equals the total number of headway observations and θj is the conditional probability function of vehicle j, as calculated by Equation (3).

The mathematical development and derivations from the original Kaplan-Meier survival function leading to the modified formula in Equation (6) are discussed in detail in the article by Hoogendoorn (2005). With the free speed survival function established, the cumulative free speed distribution function $F_{\infty}(v^0)$, which will also henceforth be referred to as the cumulative desired speed distribution function $F_d(v)$ based on the initial assumption of equivalency, is thus given by

$$F_{\infty}(v^0) = F_d(v) = 1 - \prod_{j=1}^{n_{v^0}} \left(\frac{n-j-1}{n-j-\theta_j} \right) \tag{7}$$

Going back to the theoretical foundation of speed-based following as illustrated in Figure 4, Equation (5) expresses the speed-based conditional following probability function as the integral of the desired speed probability density distribution function $f_d(v)$ between the speed v_i to infinity. Since the cumulative desired speed distribution function $F_d(v)$ is simply the integral of $f_d(v)$, Equation (5) can thus also be expressed as

$$P(Foll \mid v_i) = 1 - F_d(v) = S_d(v) = P(Foll_{speed}) \tag{8}$$

2.3 Follower Recognition

This study proposes a more general definition of a following vehicle, which suggests that a follower is a vehicle traveling below the driver's desired speed at his preferred following headway. This goes beyond having a single headway value as the sole basis of the vehicle-following condition. This definition does not specify any critical value for either headway or speed, to take into account the variability of these flow parameters. Thus, a more sensible way of determining a vehicle's following state is to do it probabilistically.

In probability theory, an event is defined as a set of outcomes to which a probability is assigned. The statistical independence of two events means that the occurrence of one event will not, in any way, affect the occurrence of the other. This basically states that two given events A and B are independent if and only if

$$P(A \cap B) = P(A)P(B) \tag{9}$$

If we assume that A is the event that a vehicle is identified as a follower based on a headway value alone, or $A = Foll_{headway}$, and B is the identification of a follower based on a speed value alone, such that $B = Foll_{speed}$, it can then be safely deduced that a vehicle's following state for each event do not influence each other since two different variables (headway and speed) are being used to identify a follower. This implies that events $Foll_{headway}$ and $Foll_{speed}$ are statistically independent of each other and this has been proven in a recent study (Catbagan, 2008). Equation (9) can thus be rewritten, such that

$$P(Foll_{headway} \cap Foll_{speed}) = P(Foll_{headway})P(Foll_{speed}) \tag{10}$$

The probability functions at the right-hand side of Equation (10) are equivalent to the theoretical functions given in Equations (3) and (8), respectively, such that $P(Foll_{headway}) = \theta(t)$ and $P(Foll_{speed}) = S(v)$. Substituting the corresponding functions to Equation (10), the following probability of any vehicle based on both headway and speed, given by $P(Foll|t,v)$ can therefore be expressed as:

$$P(Foll \mid t, v) = \theta(t) \cdot S(v) \tag{11}$$

where $\theta(t)$ and $S(v)$ are the headway-based and speed-based following probability models, respectively. The succeeding chapter discusses the specification of the functional forms of both $\theta(t)$ and $S(v)$, including parameter estimations.

The resulting figure obtained from Equation (11) is a probability value and to identify a follower with 100% certainty and reliability every time is virtually impossible. A probability threshold must therefore be established to recognize (or predict with a quantified certainty) whether a vehicle is following or not. An analysis on possible threshold values was conducted in a separate study (Catbagan, 2008), where follower counts based on various thresholds were compared with the 'expected' number of followers (or the cumulative following probability) in 5-minute intervals. A probability threshold range of 0.5-0.6 was found to be appropriate, although the threshold value of 0.5 was ultimately suggested to be more suitable for practical use and is also applied in this study for follower identification.

3. MODEL DEVELOPMENT

Now that the theoretical bases for a new follower identification methodology have been set, the actual models to be used should then be specified based on empirical data.

3.1 Categorizing Driving Conditions

Prior to model development and parameter estimation, the collected data was initially classified according to different driving conditions. The data used for this study were those collected from May to October 2006. These are data taken for each vehicle that passed through the section during this study period, which includes time of passage, speed and vehicle length. Initially, the data were categorized into 64 distinct driving conditions based on time period (holiday/weekday), ambient light (daytime/nighttime), vehicle type (PC/HV), immediate lead vehicle type (PC/HV), weather (rain/no rain) and gradient (upgrade/ downgrade). Holidays consist of all weekends and national holidays while weekdays are all the days from Monday to Friday, excluding national and special holidays. Daytime is the period from 8:00 AM to 4:00 PM while nighttime is from 8:00 PM to 4:00 AM, respectively. The 'transition' periods, 4:00 – 8:00 AM and 4:00 – 8:00 PM, were excluded to eliminate possible errors caused by the shift from daytime to nighttime and vice versa. Vehicle types of

both the subject vehicle and the immediate lead vehicle were also classified into either passenger car or heavy vehicle. Different vehicle types may prefer different tracking headways depending on the type of vehicle immediately in front of them. Weather classifications are simply divided into two – wet and dry, or rain and no rain. Each lane has also been distinguished according to gradient conditions, with the northbound lane as the upgrade section and the southbound lane as the downgrade section.

These classifications are shown in Table 1 where all data sets are represented, each having samples ranging from 800 to over 100000. However, it was later found that despite having collected a relatively large number of samples, some data categories (or driving conditions) have to be excluded from the analyses due to some inconsistencies. The effects of rain on headway preferences were investigated but the analysis produced results that do not seem to logically match with reality (e.g. lower tracking headway preferences during periods with rain). This could be due to the fact that there were relatively much fewer observed data during rainy periods compared to periods with no rain. Additionally, the data sets in the 'Rain' category have not been further classified into different rain intensities. Some previous studies have suggested that low intensity rain (0 to 2-mm) have very little or insignificant effect on traffic flow characteristics while strong rains significantly affect speed and capacity (Chung *et al*., 2006; Hong and Oguchi, 2007). Due to these issues, it was decided to eliminate the data sets under the 'Rain' category while additional data are collected for future analyses of re-classified data according to various rain intensity intervals. Similarly, it was mentioned earlier that the data in the northbound lane (upgrade) will also be excluded. The free speeds in this lane are considerably affected by gravity and are beyond the control of the drivers, so the assumption of equivalency between free speeds and desired speeds is no longer applicable in this case. Future analyses should therefore also focus on determining appropriate adjustment factors for desired speeds due to gradient effects by collecting more data from additional upgrade sections.

Thus, after taking out the discarded data, 16 driving conditions are left for the initial model development and are denoted by check marks in Table 1.

Table 1 Data set classifications for analysis

Direction/ Gradient	Weather	Leader Type	Holiday				Weekday			
			Daytime		Nighttime		Daytime		Nighttime	
			PC	HV	PC	HV	PC	HV	PC	HV
South-bound/ -3.66%	No Rain	PC	✓	✓	✓	✓	✓	✓	✓	✓
		HV	✓	✓	✓	✓	✓	✓	✓	✓
	Rain	PC	×	×	×	×	×	×	×	×
		HV	×	×	×	×	×	×	×	×
North-bound/ +4.44%	No Rain	PC	×	×	×	×	×	×	×	×
		HV	×	×	×	×	×	×	×	×
	Rain	PC	×	×	×	×	×	×	×	×
		HV	×	×	×	×	×	×	×	×

Note: Boxes with × marks denote discarded data sets

It is also important to mention that the nomenclature convention *XX_YY* shall be henceforth used to denote vehicle type *XX* with an immediate lead vehicle of type *YY*. For example, *PC_HV* means a passenger car (PC) with a heavy vehicle (HV) as its immediate lead vehicle.

3.2 General Form of the Models and Parameter Estimation

Equations (3) and (8) were used to generate points, processed from the collected data. The resulting plots were then specified into functional forms so that these can be used as probability models for follower recognition. Two base cases were selected to provide a benchmark that will serve as the ideal driving condition for both vehicle types PC and HV. The most appropriate category (or data set) closest to this condition is the one in the southbound lane on a weekday, without rain and having a passenger car as the immediate lead vehicle (i.e. *Southbound, Weekday, Daytime, No Rain, XX_PC*).

The headway-based following probability model $\theta(t)$, based on the results of numerous trials, takes the form of either a 2nd or 3rd degree polynomial function bounded by the first quadrant and $\theta(t) = 1$, with the constraint t > 0. Therefore, its general form can be expressed as

$$\theta_i(t) = \alpha_i t^3 + (b_B + \beta_i)t^2 + (c_B + \chi_i)t + 1 \tag{12}$$

where

$\theta_i(t)$	: headway-based following probability at condition i
b_B, c_B	: coefficients of base cases (*PC_PC* and *HV_PC*)
α_i, β_i, χ_i	: adjustment factors for condition i; zero at base case; $\theta(t)$ becomes a 2nd degree function at $\alpha_i = 0$

With desired speed assumed to be the sustained, maximum speed of a driver in a highway, its distribution can be considered to be part of the family of extreme-value distributions. A key feature of such distribution types is that very large values have a much greater chance of occurring than very small values (Gumbel and Lieblein, 1954). This is especially true for desired speeds. Almost all road users would like to reach their destinations at the fastest possible time, thus the higher speed preferences. Among the three extreme-value distribution types, the one that had the best fit (and also the more logical choice since the extreme-value of interest is positive) is the Type I distribution, also called the Gumbel distribution, which takes on the following form

$$F(v) = \exp\left[-\exp\left(-\left(\frac{v-\mu}{\sigma}\right)\right)\right] \tag{13}$$

where

v	: speed (km/h)
μ	: location parameter
σ	: scale parameter ($\sigma > 0$)

Similar to the generalized headway-based model, if the adjustment factors for different driving conditions are taken into account in the speed-based following probability model $S(v)$, a more generalized form of the survival function of Equation (13) (i.e. $S(v) = 1 - F(v)$) can be expressed as

$$S_i(v) = 1 - \exp\left\{-\exp\left[-\left(\frac{v-(\mu_B + m_i)}{\sigma_B + s_i}\right)\right]\right\} \tag{14}$$

where

$S_i(v)$	: speed-based following probability at condition i
σ_B	: scale parameter ($\sigma > 0$) of the base cases
μ_B	: location parameter of the base cases
s_i	: scale parameter adjustment factor for condition i

m_i : location parameter adjustment factor for condition i

Parameters for both the headway and speed-based models were empirically derived from the observed data at Route 19. With the data sets under rainy conditions and those in the northbound (upgrade) direction excluded, 16 models were developed, including the two base models. To emphasize the distinction between the 16 different driving conditions (denoted as i), the following probability model shown in Equation (11) can thus be rewritten as

$$P_i(Foll \mid t, v) = \theta_i(t) \cdot S_i(v) \tag{15}$$

where

i : one of 16 pre-defined driving conditions
$P_i(Foll|t, v)$: following probability at condition i
$\theta_i(t)$: headway-based following probability at condition i
$S_i(v)$: speed-based following probability at condition i

Table 2(*a*) lists the adjustment factors for the coefficients of the headway-based following probability model $\theta i(t)$. The base models for the passenger car and heavy vehicle are also included with the base case coefficients b_B and c_B already in place. The base model coefficients for the passenger car are b_{B_PC} = -0.011 and c_{B_PC} = 0.0076, while the base model coefficients for the heavy vehicle are b_{B_HV} = -0.0102 and c_{B_HV} = 0.0153. Positive coefficients generally indicate positive contribution to (or an increase in) following probability for any given t, while negative coefficients have the opposite effect (decrease in probability).

Table 2 Model adjustment factors

(*a*) $\theta_i(t)$ Coefficients

		Passenger Car (PC) $\theta_i(t)_{PC} = \alpha_i t^3 + (-0.011 + \beta_i)t^2 + (0.0076 + \chi_i)t + 1$						Heavy Vehicle (HV) $\theta_i(t)_{HV} = \alpha_i t^3 + (-0.0102 + \beta_i)t^2 + (0.0153 + \chi_i)t + 1$					
		PC_PC			PC_HV			HV_PC			HV_HV		
		α_i	β_i	χ_i	α_i	β_i	χ_i	α_i	β_i	χ_i	α_i	β_i	χ_i
Holiday	DT	0	0.0006	0.0073	0	0.0009	0.0081	-0.0004	0.0047	-0.0085	0	0.0008	0.0074
	NT	-0.0004	0.0053	0.002	0	0.0029	0.0108	-0.0008	0.0108	-0.0163	-0.0005	0.0107	-0.0145
Weekday	DT	0	0	0	0	0.0017	-0.0011	0	0	0	0	0.0012	0.006
	NT	0	-0.0001	0.007	-0.0002	0.0061	0.0016	-0.0004	0.0067	-0.0054	-0.0004	0.0081	-0.0087

(*b*) $S_i(v)$ Coefficients

		Passenger Car (PC) $S_i(v)_{PC} = 1 - \exp\left\{-\exp\left[-\left(\frac{v-(65.675+m_i)}{7.7667+s_i}\right)\right]\right\}$				Heavy Vehicle (HV) $S_i(v)_{HV} = 1 - \exp\left\{-\exp\left[-\left(\frac{v-(65.169+m_i)}{9.3723+s_i}\right)\right]\right\}$			
		PC_PC		PC_HV		HV_PC		HV_HV	
		s_i	m_i	s_i	m_i	s_i	m_i	s_i	m_i
Holiday	DT	0.8565	3.034	0.7964	3.383	1.2527	3.33	1.8617	6.267
	NT	0.1084	3.524	0.1952	4.794	-1.041	1.327	-0.1852	4.625
Weekday	DT	0	0	0.3823	0.834	0	0	1.9787	4.618
	NT	-0.1253	0.075	1.0885	3.262	-0.7494	-0.57	0.4253	-0.317

Note: Base conditions have zero values for all coefficients and are shaded in gray.

Similarly, Table 2(*b*) lists the adjustment factors for the speed-based following probability model $S_i(v)$ under driving condition *i*. The base model coefficients for the passenger car are σ_{B_PC} = 7.7667 and μ_{B_PC} = 65.675, while the base model coefficients for the heavy vehicle are σ_{B_HV} = 9.3723 and μ_{B_HV} = 65.169. Positive values for the scale and location adjustment factors (s_i and m_i, respectively) generally mean increased following probabilities, while negative values mean lower probabilities relative to the base scenario.

4. CURRENT AND PROPOSED METHODOLOGY – A COMPARISON

With the proposed follower identification procedure in place, follower density can now be re-calculated. It is important to note that although the calculation of follower density itself has not changed from the original procedure, the definition of followers has been totally modified.

From the previously used single critical headway values that define followers, the re-calculated follower density considers not only the variation in preferred tracking headways between various drivers, but also the drivers' different desired speeds. Moreover, the variations of both parameters for each driver type given a specified driving condition were also taken into account. For example, a driver driving at night on a holiday while following a heavy vehicle may have different following headway and speed preferences while driving during daytime on an ordinary weekday with another passenger car as a lead vehicle. The resulting number of followers can thus be said to have been normalized, taking away the bias created by the factors affecting drivers' perception of following and making it possible to identify followers at any given time or driving condition, much more realistically than before. Table 3 summarizes the differences between the two methodologies in terms of factors considered.

Table 3 Comparison of existing and proposed follower identification methodologies in terms of factors considered

Factors Considered	Follower Identification Methodology	
	Single Headway Value	Following Probability
Preferred following headway variability	×	✓
Desired speed variability	×	✓
Driver type (holiday or weekday drivers)	×	✓
Ambient light conditions (daytime or nighttime)	×	✓
Vehicle type and immediate lead vehicle type	×	✓
Gradient	×	*
Weather	×	*

**Considered but needs further study and development*

The difference in the process was also quite evident when comparing the analysis results of both methodologies. With the HCM 3-second threshold, any vehicle having a headway value

of 3-seconds or less, regardless of the prevailing conditions, will be identified as a follower. The proposed procedure on the other hand, considers not only the headway of each vehicle but also its present speed. Figure 5 shows a partial snapshot of the follower identification results based on both the HCM and the proposed methodologies. It can be clearly seen from the figure how using the single headway value as the sole basis for follower identification differs from the procedure that bases its follower identification decision on both headway and speed in equal weight and importance.

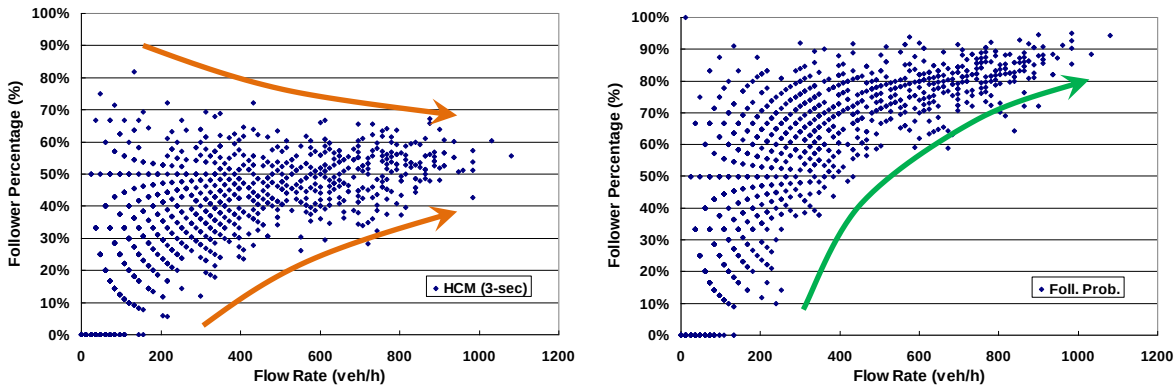
Date and Time	Speed (km/h)	Length (m)	Type	Headway	$\theta(t)$	$S(v)$	P(Foll)	$Foll_{prob}$	$Foll_{3-s}$
2006/5/3 2:21:12.30	71.1	5.5	HV	7.95	0.786731	0.579994	0.456		
2006/5/3 2:22:28.45	64.7	17.7	HV	76.15	0	0.824659	0.000		
2006/5/3 2:22:31.25	59.3	3.6	PC	2.80	0.988016	0.982864	0.971	1	1
2006/5/3 2:24:52.29	64.7	10.9	HV	141.04					
2006/5/3 2:24:54.28	71.1	4	PC	1.99				1	1
2006/5/3 2:24:57.50	64.7	12.6	HV	3.22	0.			1	
2006/5/3 2:25:00.38	70.6	14.6	HV	2.88	0.			1	1
2006/5/3 2:25:33.60	71.1	3.7	PC	33.22					
2006/5/3 2:26:28.57	64.3	2.8	PC	54.97					
2006/5/3 2:26:38.15	64.7	8.5	HV	9.58	0.342111	0.710781	0.243		
2006/5/3 2:26:40.65	70.6	12.6	HV	2.50	0.997313	0.599886	0.598	1	1
2006/5/3 2:26:42.51	78.8	5.8	HV	1.86	1	0.31285	0.313		1
2006/5/3 2:26:45.04	78.8	7.8	HV	2.53	0.997127	0.31285	0.312		1
2006/5/3 2:27:00.35	78.3	4.4	PC	15.31	0	0.312008	0.000		
2006/5/3 2:27:20.92	71.1	4.3	PC	20.57	0	0.544123	0.000		
2006/5/3 2:28:37.15	88.5	3.6	PC	[illegible]	[illegible]	[illegible]	0.000		
2006/5/3 2:28:56.55	71.1	11.2	HV	[illegible]			0.000		
2006/5/3 2:28:59.26	70.6	9.6	HV	[illegible]			0.597	1	1
2006/5/3 2:29:48.48	44.4	2.3	PC	[illegible]			0.000		
2006/5/3 2:31:42.41	87.8	9.4	HV	[illegible]			0.000		
2006/5/3 2:35:12.56	32.3	5.2	HV	[illegible]			[illegible]		
2006/5/3 2:36:01.63	64.3	4.4	PC	[illegible]	[illegible]	[illegible]	[illegible]		
2006/5/3 2:36:03.17	59.3	3.6	PC	1.54	0.999805	0.970248	0.970	1	1
2006/5/3 2:36:06.03	71.1	13.2	HV	2.86	0.983333	0.437544	0.430		1
2006/5/3 2:36:10.03	64.3	10.3	HV	4.00	0.9792	0.837731	0.820	1	
2006/5/3 2:36:13.52	64.7	14.5	HV	3.49	0.987628	0.824659	0.814	1	
2006/5/3 2:36:15.54	59	4.8	PC	2.02	1	0.985342	0.985	1	1
2006/5/3 2:36:47.05	54.8	2.4	PC	31.51	0	0.998019	0.000		

- Identified as followers by the HCM method
- Identified as non-followers by the proposed method, mainly due to high speeds

- Identified as non-followers by the HCM method
- Identified as followers by the proposed method, due to relatively low speeds

Figure 5 Snapshot of follower identification results – comparison of HCM follower definition (3-sec) and the proposed methodology

Relationships between follower flow and basic flow parameters were also compared. Follower percentage relationships with flow rate (taken during a one week peak holiday period in Japan) based on both follower identification methodologies are shown in Figure 6. The first chart (*a*), based on the HCM 3-second threshold, illustrates a rather odd trend with follower percentage values converging around the 50-60% range (note the orange arrows). The second chart (*b*) is based on the following probability concept being proposed in this study with the resulting scatter plots exhibiting a more logical behavior. It is normal to have large follower percentage variations in low-flow conditions, as seen in both charts, but as flow rate increases, these variations should decrease and converge to around 90-100% (note the green arrow) when volumes approach capacity.

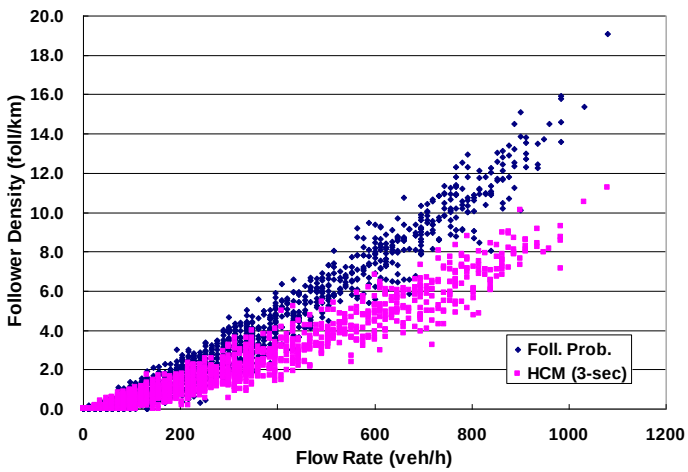


(a) *(b)*

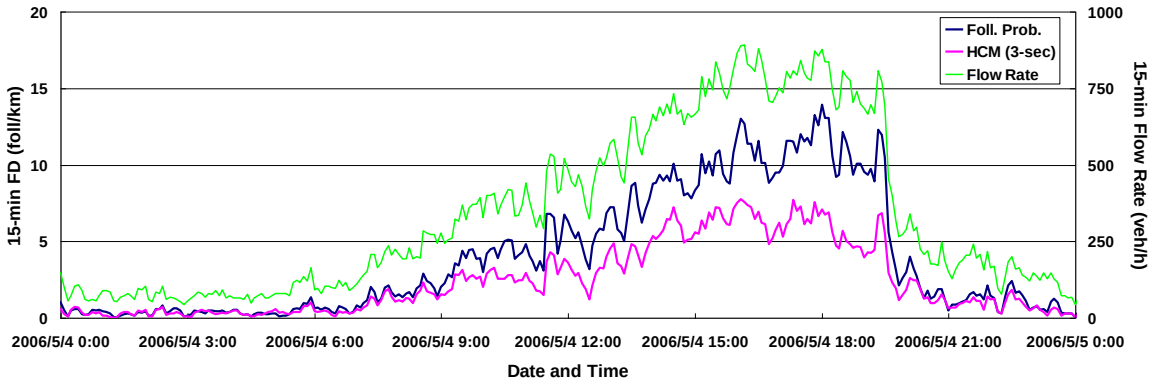
Figure 6 Follower percentage relationship with flow rate (peak period – GW, 2006): Comparison of *(a)* HCM methodology (3-sec) and the *(b)* proposed methodology (following probability)

Follower density values were calculated based on the proposed methodology and compared with follower density values calculated using the HCM 3-second critical headway. The resulting plots are shown in Figure 7(*a*), where it can be seen that the difference in follower density values between the two methodologies increase as flow rates increase. This implies that follower flow is being underestimated if the 3-second critical headway is used for follower identification, especially at high flow rates. This is rather expected given that only headways are considered in the HCM procedure. During heavy flow, a considerable number of following vehicles are likely to have preferred following headways higher than 3 seconds but are already traveling below their desired speeds. However, if vehicle following is only based on a single headway value, such as the 3-second threshold, such cases of following behavior will never be recognized.

A similar comparison of follower density values, this time in 15-minute intervals, on a typical day during a peak holiday period (in this case, the Golden Week) is shown in Figure 7(*b*). Again, the lower follower density estimates using the 3-second threshold is evident. The plot of the corresponding 15-minute flow rate is also included in the chart to show that the follower density trend follows the behavior of flow rate, especially at relatively high volumes.



(a) 5-minute follower density relationships with flow rate (*peak period – GW, 2006*)



(b) 15-minute follower densities and flow rate on a typical day during peak period (GW, 04 May 2006)

Figure 7 Comparison of follower densities calculated using different procedures

5. CONCLUSIONS AND RECOMMENDATIONS

This study was mainly based on the proposed definition of a following vehicle, which states that *a follower is a vehicle traveling below its desired speed at its preferred tracking headway*. This definition was deemed more suitable as it generalizes the concept of vehicle following in the context of service quality in two-lane highways. To complement this generalized definition, an improved follower identification methodology, based on both headway and speed was developed. Since the current practice of using single headway values for follower identification has been considered to be too simplistic and unrealistic, a probability-based method of identifying following vehicles was found to be a more reasonable way of analyzing follower flow to evaluate quality of service in two-lane highways.

Sixteen (16) following probability models, representing different driving conditions, were used to estimate follower flow parameters, such as *follower percentage* and *follower density*. Since the proposed methodology considers not only the variation of preferred tracking headways between drivers but also the randomness of drivers' desired speeds, the resulting follower flow parameters were seen to be more accurate and more reliable than previous results. The bias created by factors affecting drivers' perception of following have been eliminated, making it possible to identify followers more logically (theoretically) at any given time or driving condition.

Potential use in quantifying user satisfaction can also be explored in future studies since the proposed procedure estimates the probability that a vehicle is following – an indication of the level of driver satisfaction.

During the course of this study, it was necessary to exclude the data sets under the upgrade section and those covered by rainy conditions. It is therefore recommended to develop additional models covering these factors by collecting more data. Analyzing at least several sites is required to extract the adjustment factors due to gradient. Rainy conditions should also be categorized further into different rainfall intensities to determine the corresponding effects of various amount of rainfall.

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