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A State-of-the-Art Review of Car-Following Models with Particular Considerations of Heavy Vehicles

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ABSTRACT *Car-following (CF) models are fundamental in the replication of traffic flow and thus they have received considerable attention. This attention needs to be reflected upon at particular points in time. CF models are in a continuous state of improvement due to their significant role in traffic micro-simulations, intelligent transportation systems and safety engineering models. This paper presents a review of existing CF models. It classifies them into classic and artificial intelligence models. It discusses the capability of the models and potential limitations that need to be considered in their improvement. This paper also reviews the studies investigating the impacts of heavy vehicles in traffic stream and on CF behaviour. The findings of the study provide promising directions for future research and suggest revisiting the existing models to accommodate different behaviours of drivers in heterogeneous traffic, in particular, heavy vehicles in traffic.*

1. Introduction

Car-following (CF) models form an underlying component of microscopic traffic simulations, which enable transport engineers to replicate the dynamic behaviour of travellers at small discrete intervals. Most CF models look at within lane behaviour and represent the interactions between two successive vehicles. In particular, they have a significant impact on the ability of traffic micro-simulations to replicate real-world traffic behaviour.

Brackstone and McDonald (1999) presented a comprehensive bibliography of CF models in 1999. Since then, new methods have been developed and/or some modifications to CF models have been conducted which improve the replication and prediction of driver's behaviours. Furthermore, recent studies highlighted the impacts of the presence of heavy vehicles on behaviours of drivers and more specifically during the CF process. Given that 15 years have passed since this review and that freight vehicles have become a more important part of the traffic stream, it is appropriate to review the existing models and include the literature considering the interactions between heavy vehicles and passenger cars. The findings of this study provide an indication of directions for future research.

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Section 2 presents the definition of the CF process and provides a general overview of the existing models. Sections 3 and 4 cover the review of existing CF models and categorize them into two main groups: *classic models* and *artificial intelligence models*. Section 5 presents the impacts of vehicular heterogeneity on CF behaviours and discusses future directions to improve CF models. This paper closes with some concluding remarks.

2. CF Models Overview

In CF models, vehicles are described by a vector of state variables $(x_n, v_n, a_n,\ t_n)$ which provides the spatial location (x_n), the speed (v_n), and the acceleration (a_n) of the nth vehicle whilst they move along the road within a lane. A model then consists of a set of rules or equations to update these quantities over time (t_n).

Figure 1 illustrates the CF process for vehicle (n) following vehicle $(n-1)$. The vehicles move from left to the right in this figure. The magnitude of x increases from left to right and the vehicles are numbered from right to left. This corresponds to the temporal sequence in which they pass a standing observer. Other dimensions used in CF are front-to-front bumper distance (or relative spacing $\Delta x = x_{n-1} - x_n$) and relative speed $(\Delta v = v_{n-1} - v_n)$ between (n)th and $(n-1)$th vehicles in which vehicle $(n-1)$ is the vehicle immediately in front of the (n)th vehicle.

Existing CF models were categorized into the two main groups in this paper: classic and artificial intelligence models. The classic models use mathematical equations to replicate CF, and include stimulus–response, safe-distance, desired headway, and psychophysical models. The artificial intelligence models which are rule based and need computer algorithm for prediction include fuzzy logic and neural networks models. Table 1 summarizes these models presenting the general procedure used in each group and the associated characteristics.

3. Classic Models

In this type of CF models, the action of the subject vehicle is related to the action of the leading vehicle by a number of mathematical equations. The history of these models reaches back to the 1960s–1980s although some of them have been modified or developed further in recent years. Due to the structure of classic models in which analytical equations are provided, they are generally easier to comprehend and work with compared with artificial intelligence models which rely on computer programming. This class of models is widely used and forms the bases of commonly used commercial micro-simulations packages such as VISSIM, AIMSUN,

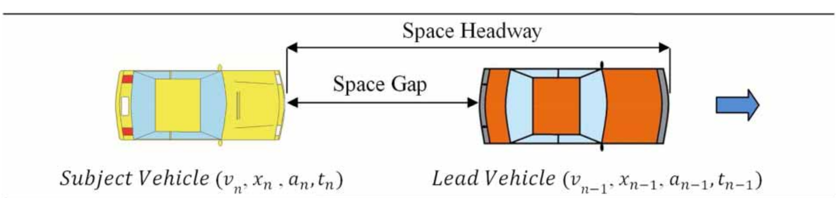

Figure 1. Sketch of CF.

Table 1. Summary of existing car-following models

The Types of Car-following Models					
Classic				Artificial Intelligence	
Stimulus response	Collision avoidance	Desired headway	Psychophysical	Fuzzy Logic	Neural Network
Some of related literature • GHR model: Chandler et al (1958) • Hoefs (1972) ; Aron (1988) • Linear model (Helly 1959) • Optimal velocity (Bando et al 1995) • IDM (Treiber et al 2000)	Pipes (1953) Kometani & Sasaki (1959) Gipps (1981)	Bullen (1982)	Michael (1963) Wiedmann (1974) Espie et al (1994)	Kikuchi & Chakroborty (1992) McDonald, Wu, and Brackstone (1997)	Hongfei et al (2003) Panwai and Dia (2007)
General procedure of the model The response of following vehicle is related to some stimulus Response is the acceleration of following vehicle Stimulus may include: • The vehicle speed • Relative speed between the subject vehicle and its leader • Relative position between them	A following driver keeps a safe distance to avoid a collision (Kometani & Sasaki, 1959): Safe distance at (time t-T) is related to: • Subject vehicle velocity at time t • Its leader velocity at time t-T (T is the reaction time) Gipps (1981): Safe speed to keep safe distance Related to: distance between the two successive vehicles and their accelerations and speeds	Drivers' attempt to maintain fixed time headway between their vehicle and their leader.	Drivers' react according to the visual angle changes made by the lead vehicles (Michael 1963) Presenting 4 acceleration behaviour for 4 different regimes: (Wiedmann 1974): • Uninfluenced driving • Closing process • Following process • Emergency braking	Applying fuzzy sets and fuzzy rules instead of precise magnitudes and equations: • Distance :very small, small, adequate, more than adequate, large & very large • Relative speed: the subject is slower, slightly slower, near zero, slightly faster, quite faster & faster • Acceleration/ Deceleration: Strong, somewhat strong, normal, mild, very mild, none	Adaptive system and change the structure during the learning phase (Training and Testing) (Hongfei et al 2003): Back propagation learning algorithm Inputs: relative speed and distance between the two vehicles, the subject vehicle current speed and its desired speed Output: acceleration

Specific capabilities of the model					
• Transparent theory • Simple to use and calibrate • Make sense • Easy verification	• Reasonable and scientific based • Simple to understand • Make sense • Easy to use	• Very simple • Easy to use	• Considering different regimes and conditions • Considering different behaviour in each regime	• Considering human imprecise perception	• Considering human imprecise perception • Modelling complex non-linear relationships • Handling large number of variables • Adaptive system and Self-learning
Specific issues need further consideration					
• Drivers detect even small magnitudes of stimulus and react • Not considering drivers' imperfect perceptions • Using a global model for different conditions, drivers and vehicles	• Under-estimated capacity (Drivers do not usually keep the safe distance presented in these models) • Not consider drivers perception and any small changes may end to reaction	• Very simple assumption and disregarding many factors • No calibration method for different conditions and drivers • Small changes may end to driver's reaction	• Existence of the rules makes the model more difficult to understand and apply without computers • need to consider different regimes for different types of vehicles and drivers	• Difficulties in validation of membership functions • Difficulties in determining of Fuzzy rules • Existing models do not consider different vehicle types	• Risk in learning process due to "under-study" and "over-study" • Could be used only with computer • need to consider different types of vehicles and drivers

and PARAMICS. The different modelling approaches in this class are described as follows.

3.1. *Stimulus–Response Models*

This type of models is one of the first CF models developed to replicate CF behaviours of drivers. The subject vehicle driver's action (response) is directly related to the stimulus created by the leading vehicles' behaviour. In general, the response is deceleration or acceleration of the subject vehicle is delayed by an overall reaction time, T. The stimulus may include the relative speed and/or spacing between the subject vehicle and its leader. This type of models has been developed and used in a wide range of CF behaviour predictions. Four major subgroups of stimulus–response models are reviewed.

3.1.1. *Gazis–Herman–Rothery model*. The Gazis–Herman–Rothery model (GHR model) was first introduced by Chandler, Herman, and Montroll (1958) at General Motors research laboratories and at the same time in Japan by Kometani and Sasaki (1958). The general formulation of this model is

$$a_n = cv_n^m(t)\frac{\Delta v(t-T)}{\Delta x^l(t-T)}, \tag{1}$$

where a_n is the acceleration of the (n)th vehicle at time t, v_n is the velocity of the (n)th vehicle, $\Delta x = x_{n-1} - x_n$ is the relative spacing between (n)th and $(n-1)$th vehicles, $\Delta v = v_{n-1} - v_n$ is relative speeds between (n)th and $(n-1)$th vehicles, T is the driver's reaction time, and c, m, and l are model calibration parameters.

Calibration parameters for these models have been proposed by many authors. Chandler et al. (1958) proposed that m and l were equal to zero. In the calibration, vehicles linked by wires were used to examine the responses of 8 test subjects to a realistic speed profile of a lead vehicle over a 30-minutes period on a test track. The speed of vehicles varied from 10 to 80 mph (16.1–128.7 km/h). Gazis, Herman, and Potts (1959) used the microscopic equation as a starting point to find a macrosclopic relation between speed and flow. The results were not properly matched. Subsequently, they found a better result with a hypothesis suggested that the acceleration should be inversely related to Δx. This was confirmed by Herman and Potts (1959), who gained a better fit for $l = 1$.

Edie (1960) applied the model proposed by Gazis et al. (1959) to match a new set of macroscopic data. He found that if the relative speed of the vehicles entered as a term in the microscopic equation, the calibration would improve. He produced a model that applied for the first time all terms of equation 3.1 by proposing $m = 1$ and $l = 1$.

Afterwards, many other authors (Aron, 1988; Ceder & May, 1976; Heyes & Ashworth, 1972; Hoefs, 1972; May & Keller, 1967; Ozaki, 1993; Treiterer & Myers, 1974) calibrated the model with different data sets and methods. Among these studies, Hoefs (1972) and Aron (1988) applied this type of model with major additional contributions.

This type of stimulus–response models has no preferred distance. This means that if $\Delta v = 0$, the relative position of the vehicles will remain constant. Furthermore, the model does not have any acceleration or deceleration limits. This is important when the traffic is mixed because in reality accelerations and decelerations are restricted by vehicle characteristics.

3.1.2. *Linear (Helly) model*. Helly (1959) added some terms into the first GHR model to adapt the acceleration of the subject vehicle with consideration of its leading vehicle braking. A simplified version of this model is

$$a_n(t) = c_1 \Delta v(t-T) + c_2[\Delta x(t-T) - D_n(t)], \tag{2}$$

where a_n is the acceleration of the nth vehicle at time t, $\Delta v = v_{n-1} - v_n$ is relative speeds between (n)th and ($n-1$)th vehicles, $\Delta x = x_{n-1} - x_n$ is the relative spacing between (n)th and ($n-1$)th vehicles, T is the driver's reaction time, c_1 and c_2 are model calibration parameters; and $D_n(t)$ is a desired following distance formulated by

$$D_n(t) = \alpha + \beta v_n(t-T) + \gamma a_n(t-T), \tag{3}$$

where v_n is the velocity of the nth vehicle; and α, β, and γ are calibration parameters.

Hanken and Rockwell (1967) and Rockwell, Ernst, and Hanken (1968) used a wire linked vehicle, similar to what had been used by the earlier General Motors team to calibrate this type of model on an urban freeway. The model was calibrated for congested and uncongested traffic conditions.

Later, Bekey, Burnham, and Seo (1977) calibrated this type of models from the design of optimal control systems and by tracking 125 vehicles over 4 minutes. It was reported that the model could replicate trajectories quite well, but was a bit smooth in the transition between acceleration and deceleration regions.

Further studies of linear models were combined with GHR models. Xing (1995) developed a model based on this combination and calibrated the model by using the data recorded from 500-meters section of a road. This model contains four main terms. The first term captures standard driving. It relates the acceleration to the relative speed between two successive vehicles and the inverse of the space between them. The second term captures the situation where a standing subject vehicle accelerates from a queue. The model has also one term for the free flow situation and one term to consider the impact of gradient on CF behaviour.

The previous studies conclude that although this type of stimulus–response model can replicate low-acceleration patterns, it has significant errors and creates headways larger than reality when the magnitude of fluctuations of acceleration increases.

3.1.3. *Optimal velocity model*. Another approach uses the optimal velocity. This approach generally considers the difference between the driver's optimum/desired velocity and the current velocity of the vehicle as a stimulus for driver's actions. The idea of the optimal velocity model (OVM) is based on Newell (1963) and was developed by Bando, Hasebe, Nakayama, Shibata, and Sugiyama (1995). The acceleration of a vehicle represents the driver's response and is determined by the following equation.

$$a_n = c[V_n^{\text{desired}}(t) - v_n(t)], \tag{4}$$

where a_n is the acceleration of the nth vehicle at time t, V_n^{desired} represents the desired speed of nth vehicle, v_n is the velocity of the nth vehicle, and c is the model calibration parameter.

In the GHR model, the desired speed is considered equal to the speed of lead vehicle ($v_{n-1}(t)$) but in the OV model, it is considered to be relevant to the relative spacing of the two successive vehicles. The acceleration of the following vehicle is calculated by the following equation:

$$a_n(t) = c[V^{\text{opt}}(\Delta x(t)) - v_n(t)], \tag{5}$$

where $\Delta x = x_{n-1} - x_n$ is the relative spacing between (n)th and $(n-1)$th vehicles; and $V^{\text{opt}}(\Delta x)$ is a sigmoid function of Δx.

The function was defined differently but all based on the fact that a driver maintains the vehicle velocity according to the relative position of the vehicle to keep a safe-distance. One of the calibration functions is

$$V^{\text{opt}}(\Delta x) = \begin{cases} 0 & \Delta x < \Delta x_A, \\ f(\Delta x) & \Delta x_A < \Delta x < \Delta x_B, \\ v_{\max} & \Delta x_B < \Delta x. \end{cases} \tag{6}$$

This function must be calibrated.

Lenz, Wanger, and Sollacher (1999) extended the model developed by Bando et al. (1995) to multi-vehicle interactions. As an extension of the equation, this work's drivers consider up to m vehicles ahead with sensitivity of a_j when they are following the vehicles. Their equation is presented as follows:

$$a_n(t) = \sum_{j=1}^{m} a_j \left[V^{\text{opt}}\left(\frac{x_{n+j} - x_n}{j} \right) - v_n \right]. \tag{7}$$

For $m = 1$, the result will be similar to Equation 3.6 developed by Bando et al. (1995). They defined different functions for f as the deviation of V^{opt} for different values of m.

The OVM, as a stimulus–response model, has all problems of this type of models plus it introduces unrealistically large acceleration rates (Nagel, Wanger, & Woesler, 2003). Therefore, this model has not been used broadly.

3.1.4. *Intelligent driver model*. The intelligent driver model (IDM) was developed by Treiber, Hennecke, and Helbing (2000). Although this model can be considered as a stimulus–response model, it has got some idea of safe driving which could be related to safe-distance type of CF models. The acceleration of the subject vehicle was related to its speed, v, as well relative speed and the space between the subject and lead vehicles (Δv and S). The model combined free-road acceleration with deceleration strategies. The IDM acceleration function is given by

$$a = a_0\left[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{S*}{S}\right)^{2}\right]. \tag{8}$$

In this model, the free acceleration, $a_0[1-(v/v_0)^{\delta}]$, was estimated by the maximum acceleration of the vehicle (a_0), desired speed (v_0), and the speed of the vehicle (v), whilst δ was used to characterize how the maximum acceleration of a vehicle decreases with increases in its speed. When a vehicle comes too close to its leader, the deceleration strategy of the model will apply and the vehicle will decelerate with the magnitude of $-a_0[(S^*/S)^2]$ in which S is the actual gap (see Figure 1) between the subject vehicle and its leader and S^* is the effective minimum gap which can be computed as a function of v and Δv by

$$S^* = S_0 + vT + \frac{v.\Delta v}{2\sqrt{a_0.b}}, \tag{9}$$

where T is the driver's desired minimum time headway, S_0 is the jam distance, and b is the driver's desired deceleration. Note that the driver's desired minimum time headway used in this model differs from the reaction time used. However, an effective reaction time as an optional variable can be implemented by a suitable update time in the numerical integration of the acceleration equation (Kesting & Treiber, 2008). Although this model has been used by Kesting and his colleagues (e.g. Kesting, Treiber, & Helbing, 2010), it has not been widely used by transport researchers or in commercial traffic micro-simulations.

3.1.5. *Summary*. The above discussion of stimulus–response models concludes that

- The theory behind this type of models is transparent and can be verified by the user.
- This type of models could provide some equations which are reasonable and make sense for all the readers.
- They are generally simple to understand and use.
- The calibration of this type of models is easier than other types.

However, the existing models could be improved by considering the following issues:

- The models only consider movement in a lane. This is appropriate in the modelling on road vehicle movement but may not be appropriate for other modes such as bicycle and pedestrian (see Zhang, Wang, & Li 2006 for further information for modelling bicycle and Shiwakoti, Sarvi, Rose, and Burd 2011 for pedestrian movement).
- The models assume that drivers can detect small magnitudes of stimulus and will react to these. This may not be consistent with driver behaviour since individual drivers cannot measure speed and space precisely and are therefore not very sensitive to small changes of stimulus. Indeed, they react to the actions of the lead vehicle only when the perceived stimulus exceeds a certain threshold.

Consideration this aspect of driver behaviour in more detail offers a considerable opportunity for the development of more accurate CF models in the future.
- The models estimate a single value for each of the model parameters which indicate that these models are not able to capture differences in behaviour of different drivers and different vehicle types. Again driver behaviour may not be modelled accurately.
- The models assume that the reaction time (or desired minimum time headway for the IDM) is the same for all drivers and ignores differences between drivers and vehicle types.
- Most of these models also only consider two vehicles. The interaction between a queue of vehicles on the road may differ from that of a stimulus and response vehicle.
- The reliability of these models for different vehicle classes needs investigation.

3.2. *Safe-Distance Models*

Safe-distance or collision avoidance models find a safe following distance within which a collision would occur if the lead vehicle driver behaves unpredictably; unless the subject vehicle drive keeps a longer space in front of the vehicle compared with the safe-distance when following another vehicle. This type of CF model refers to Pipes' (1953) rules

> A good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car between you and the vehicle ahead for every ten miles an hour (16.1 km/h) of speed at which you are travelling.

Kometani and Sasaki (1959) first formulated this type of model based on safe following distance using physical motion equations. According to this model, collision will be unavoidable when the leading vehicle acts unpredictably and the space headway in front of the subject vehicle is shorter than the safe-distance. Such a situation is precluded in most applications of this model; however, increasing interest in the simulation of safety (Young, Sobhani, Lenne, & Sarvi, 2014) may need this assumption to be relaxed in some situations. The safe-distance can be calculated as follows:

$$\Delta x(t-T) = \alpha v_{n-1}^2(t-T) + \beta_1 v_n^2(t) + \beta v_n(t) + b_0, \tag{10}$$

where $\Delta x = x_{n-1} - x_n$ is the relative spacing between (n)th and $(n-1)$th vehicles, v_{n-1} is the velocity of the $(n-1)$th vehicle, v_n is the velocity of the (n)th vehicle, and T is the driver's reaction time, α, β_1, β and b_0 are model calibration parameters.

Gipps (1981) developed a model based on collision avoidance comprising two constraints for the follower's (subject's) velocity:

- The speed of vehicle (n) should not exceed from its desired speed and its free acceleration should first increase with speed as engine torque increases and then decrease to zero as the vehicle approaches the desired speed.
- The following drivers must be sure that their vehicle will stop safely if the leading vehicle brakes suddenly. Previous models of this type did not contain

any margin for error. He introduced a further safety margin by proposing that the driver makes allowance for a possible additional delay before reacting to vehicle ahead. This delay considered equal to $T/2$, where T is the reaction time and constant for all drivers.

The two considerations resulted in the following formulation (Gipps, 1981):

$$v_n(t+T) = \min \begin{cases} v_n(t) + 2.5 a_n T (1 - v_n(t)/V_n)(0.025 + v_n(t)/V_n)^{1/2} \\ b_n T + \{b_n^2 T^2 - b_n [2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t) T - v_{n-1}^2(t)/\hat{b}]\}^{1/2} \end{cases}, \tag{11}$$

where a_n is the maximum acceleration which the driver of vehicle n wishes to undertake, b_n is the most sever braking that the driver of vehicle n wishes to undertake ($b_n < 0$), s_{n-1} is the effective size of vehicle $n-1$; that is the physical length plus a margin into which the following vehicle is not willing to intrude, even when at rest, V_n is the desired speed or the speed at which the driver of vehicle n wishes to travel, $x_n(t)$ is the location of the front of vehicle n at time t, $v_n(t)$ is the speed of vehicle n at time t, $\hat{b}$ is the estimation of b_{n-1} employed by the driver of vehicle n; and T is drivers' reaction time.

The first term is related to the first constrain and the second term expresses the later one.

This model type is extremely popular in commercial computer packages. Many other collision avoidance models have also been developed and used in computer simulatitons (e.g. Broqua, Lerner, Mauro, & Morello, 1991; McDonald, Brackstone, & Jeffery, 1994). Although the base of these models is reasonable, they cannot replicate real conditions in many cases as the capacity and traffic volume estimated by them are underestimates. In reality, drivers are able to use many sources of information and react accordingly. In fact, they do not have to keep the safe-distance calculated here. Furthermore, this type of models does not consider drivers' perception and any small changes may end to the reaction of the subject (following) vehicle driver. This type of model does not consider heterogeneity of drivers and vehicle types.

3.3. *Desired Headway Models*

This type of CF model is based on the assumption that a following vehicle attempts to maintain a fixed time headway between its front bumper and the rear bumper of its leader. Bullen (1982) developed a model called the 'Pitt CF model' based on this assumption. Thereby, the subject vehicle aims to have the relations presented below at time (t) and ($t+T$):

$$\begin{aligned} x_{n-1}(t) - x_n(t) - L_{n-1} &= h v_n(t), \\ x_{n-1}(t+T) - x_n(t+T) - L_{n-1} &= h v_n(t+T), \end{aligned} \tag{12}$$

where x_{n-1} and x_n are the position of the leading and following vehicles, respectively, L_{n-1} is the length of leading vehicle, v_n is the velocity of the following vehicle, and h is the fixed time headway.

From kinematics:

$$x(t+T) = x(t) + v(t)T + \frac{1}{2}a(t+T)T^2, \tag{13}$$

$$v(t+T) = v(t) + a(t+T)T. \tag{14}$$

The equation for $a_n(t+T)$ can be derived from Equations (13) and (14):

$$a_n(t+T) = \frac{x_{n-1}(t) - x_n(t) - L_{n-1} - hv_n(t) - [v_n(t) - v_{n-1}(t)]T + \frac{1}{2}a_{n-1}(t+T)T^2}{T\left(h + \frac{1}{2}T\right)}, \tag{15}$$

where a_n is the acceleration of the following vehicle and a_{n-1} is the acceleration of its leader.

This model is based on a simple assumption and there is no method for calibrating it. Different drivers in different conditions might follow their leaders, but this model is not able to capture these key points. This type of model does not consider the ability of drivers' to perceive the changes and thus any small changes can result in the following vehicle drivers' reactions. Furthermore, these models are neither able to capture the different CF behaviours of drivers in mixed traffic stream, nor the performance of the different vehicle types.

3.4. *Psychophysical Models*

The psychophysical or action points models emerged based on this assumption that drivers can estimate the lead vehicle's speed and react according to the visual angle changes made by the front vehicle. In 1963, this type of mode was introduced by Michaels (1963). These changes are calculated by Equation (16) and drivers' behaviour is modelled based on introducing some thresholds; for example, when the increasing changes exceed from a threshold, then the drivers decelerates until they do not feel any difference between their vehicle speed and its leader.

$$\mathrm{d}\theta/\mathrm{d}t = -w(\Delta v/\Delta x)^2, \tag{16}$$

where θ is the visual angle changes made by the front vehicle, w is the width of the observed object, Δv is the relative speed between the subject vehicle and its leader, Δx is the relative spacing between the subject vehicle and its leader; and t is the time.

The theory behind the visual angle models (e.g. Ferrari 1989; Michaels & Cozan, 1963; Yousif & Al-Obaedi, 2011) considers the width of vehicles to determine the safe following distance between successive vehicles. This theory implies that the space gap between vehicles become longer as the leading vehicle width increases. This may suggest that a driver will keep a longer gap in front when following a heavy vehicle compared with when the leader is a passenger car. Although, this type of model indicates that CF behaviour of drivers may differ according to their leading vehicle size (width), they are not able to capture different characteristics of heavy vehicles such as acceleration/deceleration capability; in particular, they do not differentiate between subject vehicle classes (i.e. passenger car or heavy vehicle).

One of the significant steps in the development of these models was to investigate a series of perception-based studies conducted in the early seventies (e.g. Evans and Rothery 1973). The aim of these studies was to find a set of thresholds which could quantify the driver's perception about closing to or opening from the leading vehicle. Many other studies (e.g. Burnham & Bekey, 1976; Lee, 1976; Reiter, 1994; Wiedemann, 1974; Wiedemann & Reiter, 1992; Wiedemann & Schwerdtfeger, 1987; Krauss, Nagel, & Wagner, 1999) were conducted in this category to estimate the CF thresholds and the following vehicles' acceleration. Further studies (Wiedemann & Reiter, 1992; Wiedemann & Schwerdtfeger, 1987) were conducted with the same basis (perception thresholds). One of the most popular models amongst this group is Wiedemann (1974) which is currently incorporated into the traffic micro-simulation, VISSIM, as the default CF model to update vehicle movements (VISSIM, 2012).

These models considered four different CF regimes including free driving, closing process, following process, and emergency braking. These regimes could be formed by six different perceptual thresholds. After defining and calibrating the thresholds, the situation/perception of the subject vehicle driver could be quantified at any time. This means that the model determines the regime which the driver may perceive. The behaviour of the driver and the magnitude of the vehicle's acceleration/deceleration could be estimated based on the regime.

In the other series of psychophysical CF studies, the French National Institute for Research in Transportation and Safety developed a driving behaviour model called ARCHISIM (Espie, Saad, Schnetzler, Bourlier, & Djemame, 1994). This model was based on the results of previous studies such as Leplat and Hoc (1981) and Saad (1992) and has been continued by others such as El Hadouaj, Espie, and Drogoul (2000) and Champion, Espie, and Auberlet (2001, Champion, Zhang, Auberlet, & Espie, 2002). Drivers' behaviour was observed within the complex interactions in actual conditions in two types of road situations: CF when driving on urban motorways and crossing intersections in the open country. The observed behaviour was analysed according to the interviews conducted immediately after their performance (Leplat & Hoc, 1981).

Driver behaviour in ARCHISIM was described in relation to several indicators such as speeds used, headways maintained with the lead vehicle, manoeuvres performed and traffic lanes used. The model identified four main types of intention including: maintaining speed, direction or following a route, eliminating interaction, and adaptation. Different rules were determined based on duration length of interaction and the possibility of the suppression of the interaction. The interactions can be immediate or anticipated interactions. These rules produced different intentions such as the suppression of the interaction, short-term or long-term adaptation. Several performance modes might be considered to predict driver's behaviour, but only one mode would be retained after the process which would forecast the driver's behaviour. For instance, a long duration interaction with a possibility for suppression will result in the suppression of the interaction but when it is temporarily impossible to suppress the interaction that will result a short-term adaptation.

In summary, the psychophysical CF models are able to consider human's perception better than the other classical models. So they could overcome some of the aforementioned problems of the previous models such as unrealistic sensitivity of driver's to small changes. However, the calibration of these models is more difficult compared with the other classic models. Furthermore, similar to the other models, the existing applications of these models tend to use a global set of thresholds to model CF behaviour of drivers and do not accurately replicate the differences between vehicle types.

3.5. *Summary*

The classical models have and will continue to be the building blocks of many traffic simulation models. However, the existing models could be improved by considering the following issues:

- The models only consider movement in a lane. This may be appropriate in the modelling on road vehicle movement but may not be appropriate for other modes.
- No model has yet looked at driver behaviour. They have generally looked at the outcome of this behaviour measuring vehicle characteristics such as spacing, velocity, and acceleration. This may be appropriate for normal traffic conditions but in severe situations such as vehicle conflict the driver's behaviour may be more complex, if in fact the driver is able to react. Consideration of driver behaviour in more detail offers a considerable opportunity for the development of more accurate CF models in the future.
- The models estimate a single value for each of the model parameters which indicate that these models are not able to capture differences in behaviour of different drivers and different vehicle types. Again driver behaviour may not be modelled accurately.
- The models assume that the reaction time (or desired minimum time headway for the IDM) is the same for all drivers and ignore differences between drivers and vehicle types.
- Most of these models only consider two vehicles. The interaction between a queue of vehicles on the road may differ from that of a stimulus and response vehicle. One exception being Lenz et al. (1999), which considers the interaction of multiple vehicles.
- The reliability of these models for different vehicle classes needs investigation.

4. Artificial Intelligence Models

Each of the CF models outlined above provides one or more equations to predict the behaviour of the subject vehicle driver. These models are normally easy to present and understand due to their reliance on some specific equations. However, human's behaviour is more complex than can be captured by these equations. It was necessary to develop more complex models to predict human's behaviour such as driver's CF process. To do so, several artificial intelligence models have been developed in the last two decades and are becoming more popular due to the advent of fast and more powerful computers. The artificial intelligence models are mainly based on fuzzy logic and neural network (or their combinations) which are outlined as follows.

4.1. *Fuzzy Logic Models*

Drivers' understanding and behaviour are qualitative and are sometimes based on cursory collection of data with not all factors considered. The behaviour of drivers in such situations as CF may result from their imprecise perceptions of their surrounding environments and not the real situation. For example, when drivers decide to decelerate if they are close and closing to the vehicle ahead, they may not consider the 'exact' relative speed and spacing. The drivers decide and act according to their experience, logic and judgements. Here, 'close' and 'closing' are fuzzy values and response of 'decelerate' is a fuzzy decision-making: IF 'close' AND 'closing' THEN 'decelerate'. As a result, this type of model can provide a more realistic fit with human behaviour. To consider the qualitative and fuzzy perception and decision of drivers, several fuzzy logic models have been developed and used in traffic studies.

Kikuchi and Chakroborty (1992) applied fuzzy logic rules to model CF behaviour for the first time. They employed the GHR model using the relative spacing, Δx, relative speed, Δv, and the acceleration of the lead vehicle as inputs. The quantity of the first 2 variables was grouped into 6 natural language-based categories and the last one was group into 12 categories (6 for acceleration and 6 for deceleration). Acceleration and deceleration behaviours of the leading vehicle were grouped separately because there was a belief that the reaction of the following vehicle was different in the counter facing of its leader's acceleration or deceleration.

The result of the subject vehicle's action in terms of acceleration or deceleration was predicted by a fuzzy set. The reaction of the following vehicle was similar to its leader's action in nature but might need some modification. The model provided an equation to predict the acceleration/deceleration of the subject vehicle based on the relative speed and the acceleration of the lead vehicle when the relative spacing between the vehicles was 'adequate'. This acceleration/deceleration should be modified by sliding the membership function when the relative spacing was not 'adequate'. For each deviation to a longer distance category, the acceleration was increased by 0.3 m/s^2 and for each deviation to a shorter distance category, it was decreased by 0.3 m/s^2. In this way, the model could predict the consequence of the leading vehicle action on the following vehicle by using a set of conditions represented by the input variables.

After Kikuchi and Chakroborty (1992), many other CF models (Chakroborty & Kikuchi, 1999, 2003; Das, Bowles, Houghland, Hunn, & Zhang, 1999; Gao, Hu, & Dong, 2008; Gonzalez-Rojo, Slama, Pereira, & Mora-Camino, 2000, 2002; Hatipkarasulu & Wolshon, 2003; Henn, 1995; McDonald et al., 1997; Rekersbrink, 1995; Won, Lee, Lee, & Kim, 2007; Zheng & McDonald, 2005) have been developed based on fuzzy logic rules. However, the most common problem of the fuzzy logic models group is to determine the fuzzy rules as used by a human. If the drivers' perceptions are not applied in the model properly, the model will be unrealistic and cannot predict the behaviour properly. Although some of the studies (e.g. Wu, Brackstone, & McDonald, 2003) tried to handle this problem with immediate interviews with the drivers, the validation of membership functions and the difficulties in determining of fuzzy rules have been always the major problems of this type of CF models. Furthermore, none of the above-mentioned studies considered the impacts of vehicle heterogeneity in traffic stream on the CF behaviour.

4.2. *Neural Network Models*

A neural network can be considered as a tool which tries to replicate functions of the human brain in a very fundamental manner based on neurobiological studies and modern human brain's cognitive science. Information describing a particular scenario is taken in and a decision or answer is passed out. It is tuned to perform its task correctly by experience and self-learning ability according to a large number of representative example inputs and desired decisions or answers as outputs. As a result, the model identifies the relations between a number of input parameters and the corresponding output parameters.

Neural networks were applied broadly in the field of transport in the 1990s. Among many subject areas, driver behaviour and autonomous vehicles had the highest proportion of neural network interest in the transport field (Dougherty, 1995). Pomerleau (1989 and 1992) applied neural networks in the context of developing an autonomous vehicle as opposed to modelling driving behaviour. Fix and Armstrong (1990) used neural networks for controlling a car within a very simple traffic simulation model. Training data for the neural network were collected from an individual subject driver controlling a car within the simulation. The result showed that neural networks could be applied to represent driver behaviour in models of traffic operations. Dougherty, Kirby, and Boyle (1993) showed that a network trained using 'back propagation' was able to classify congestion states. They applied neural networks to estimate flow and traffic parameters like occupancy of an urban link. The back propagation learning algorithm was named according to the way it handles the minimization of the error in the output during training. This method is the most widely applied neural network arrangement, in both research and development (Taylor, 1994).

Hongfei, Zhicai, and Anning (2003) applied the 'back propagation' algorithm to develop a CF model using data collected by a new technique named 'five-wheel system'. The relative speed and relative space between the two successive vehicles, the current speed of the following vehicle and its desired speed were used as the input variable of the model. To determine the value of desired speed, drivers were classified into three categories: risky, ordinary and conservative drivers based on the observed percentile speed. Drivers with a speed of more than 85 percentile speed were risky, less than 15 percentile were conservative and between these amounts were ordinary drivers. From these inputs, neural model predicted the acceleration or deceleration of the following vehicle as the reaction to its leader actions. They did not provide any validation to evaluate their model microscopically or macroscopically.

Panwai and Dia (2007) developed a neural networks based CF model using the data set presented in Manstetten, Krautter, and Schwab (1997). An instrumented vehicle was used to collect data during an afternoon peak on a single lane in Stuttgart, Germany. The data were recorded in 1/10th of second intervals for a total duration of five minutes. Speeds of the vehicles and the distance headway between them were used to model the CF behaviour. The model was based on maintaining desired distance headway.

The following vehicle would select its individual speed to maintain a desired distance headway described by the leader vehicle's speed and headway between the two vehicles. The performance of the developed model was evaluated using the AIMSUN traffic micro-simulation. The results showed a good fit between the real data and simulated outputs. However, it could not replicate the CF behaviour of vehicles well when they are decelerating to a stop or accelerating from stop point.

This type of models is an adaptive system which changes its structure during the learning phase. Although this characteristic could be considered as the strength of the model, it could cause the common criticism about this type of models. This criticism refers to black box in which the neural networks models could be viewed solely in terms of their input and outputs without providing any knowledge of the internal workings. The other problems of this kind of models are 'under-study' or 'over-study' phenomenon in data training process of the model. The last one can be controlled by considering the training time whilst the former one, inadequate data points, is the major problem of this kind of models. Apart from the advantages and disadvantages of the neural networks models, the developed models did not consider a specific model to capture impacts of heterogeneity on the CF behaviour.

Artificial intelligence models are not limited to fuzzy logic and neural networks. There is a potential to use their combination to model the CF behaviour. The characteristics of these models would be close to fuzzy logic or neural networks based on the specific combination. For instance, Li (2003) used fuzzy neural networks and Ma (2004) used neural fuzzy approaches for modelling of the CF process. However, these studies did not provide strong documentations and the validation of the models and their applications in traffic micro-simulations were not investigated.

Aghabayk, Forouzideh, and Young (2013) used the local linear model tree (LOLIMOT) approach (Nelles, 2001), which can be considered as a neuro-fuzzy model to model driver's CF behaviour. By this, it attempted to incorporate human perceptual imperfections into a CF model. This model defined some localities in the input space. These localities were fuzzy and had overlaps with each other. Specific models for each of the localities were then defined and combined in a fuzzy manner to predict the final output. The model was developed using real-world dynamic data sets. The performance of the model was compared with a number of existing CF models. The results showed close agreement between the real data and the LOLIMOT outputs. However, the model should be implemented in one of the microscopic traffic simulations to investigate the performance of the model in other traffic conditions and situations.

4.3. *Summary*

The artificial intelligence models have not been incorporated into many well-used simulation models due to their recent development but they offer considerable opportunities in the future. The models do, however, still have areas where they can be developed. These include as follows:

- The models only consider movement in a lane. This may be appropriate in the modelling on road vehicle movement but may not be appropriate for other modes.
- These models can replicate driver behaviour but generally use the outcomes of this behaviour, such as spacing, velocity, acceleration in their estimation. No model has yet looked specifically at driver behaviour. There is a growing interest in behaviour during crashes (Young et al., 2014) and some artificial intelligence models have been developed using data on driver behaviour in

such circumstances. This data may also be able to be used to estimate general driver behaviour during CF situations.

- The models estimate a single value for each of the model parameters which indicate that these models are not able to capture differences in behaviour of different drivers and different vehicle types. Again driver behaviour may not be modelled accurately.
- The models also only consider two vehicles. The interaction between a queue of vehicles on the road may differ from that of a stimulus and response vehicle.
- The reliability of these models for different vehicle classes needs investigation.

So far, the characteristics of the existing CF models have been presented. The summary of these models and their specific issues were included in Table 1. However, one of the general issues related to these models may be associated with considering heterogeneity in traffic stream and more specifically attractions of heavy vehicles and passenger cars. Due to an increasing number of heavy vehicles and their different characteristics compared with passenger cars, the study about heavy vehicles has become of interests of transport researchers and planners recently. Next section presents some specific studies about the CF models which may highlight a general need for further considerations of the models to enhance their accuracy and reliability.

5. Heavy Vehicles in the CF Literature

The previous models consider CF in general. However, most of the applications have focused on passenger cars. CF behaviour of heavy vehicles may differ from that of passenger cars due to both different characteristics of the vehicles such as size and acceleration/deceleration capability and the different characteristics of their drivers. In spite of the influential impacts of heavy vehicles on traffic flow, they have not received adequate attention in microscopic traffic simulations with their impact being limited to variations of coefficients within the models. This issue may need more detailed discussions and further consideration due to the growing proportion of heavy vehicles in the urban traffic stream (BTRE, 2003; NCHRP, 2003; Wright, 2006). This section reviews studies of CF behaviour where the impacts of heavy vehicles were considered in order to point to the direction new CF models of traffic flow in lanes on roads should take.

Peeta, Zhang, and Zhou (2005) considered the interaction between cars and heavy vehicles attempting to model the behaviour of passenger car drivers whilst following heavy vehicles. The study stated that the headway in front of vehicles is smaller when following a car compared with when following a heavy vehicle. To consider this interaction, an extra parameter called 'discomfort level' was defined based a survey gathered from passenger car drivers. The factors that contribute to driver's discomfort were categorized into socioeconomic characteristics, situational factors, and drivers' behavioural tendencies. The former included age, gender, education, household size, and frequency of freeway usage. The situational factors considered were bad weather (rain, snow), night driving, and three levels of traffic congestion (low, medium, and high). The discomfort factors relating to the drivers' behavioural tendencies were disregarded in this study as they were latent and could not be measured.

This study attempted to consider the impacts of heavy vehicle as the lead vehicle by introducing an extra term which resulted in a decrease in passenger car acceleration. Indeed, this study did not consider a particular formulation or model for this case and just added a supplementary term to the general model. This may not be sufficient as the behaviour of passenger cars could be fundamentally different when following heavy vehicles compared with when following another passenger car. Furthermore, this study did not considered CF behaviour of heavy vehicles at all.

Ramsay and Bunker (2007) considered heavy vehicles at arterial intersections and utilized a CF model developed by Cohen (2002). The model was an application of a CF system to queue discharge problem at signalized intersections. The acceleration of the vehicles was modelled, whilst they were discharging from an intersection. In fact, an existing CF model was used to capture queue discharge at signalized intersections modified by considering heavy vehicles' acceleration capability at intersections. Although these studies did not actually develop a CF model which could be applied in arterials links or freeways, they highlighted the different behaviours of heavy vehicles and their significant impacts on arterial traffic flows.

Yuelong et al. (2008) considered departure headway of mixed traffic flow at signalized intersections. In spite of paying attention to heavy vehicles, this paper just contained the departure headway distributions and no CF model was developed.

Sarvi and Kuwahara (2008) investigated the impacts of heavy vehicles on traffic characteristics and operation of freeway merging section under congested traffic conditions. The aim of this study was to examine the benefit of employment of intelligent transportation systems to increase the capacity of merging sections. It used a macroscopic data to determine the effect of heavy vehicles on the capacity of merging section and a microscopic data for model development. The model was developed with the consideration of heavy vehicles and suggested using variable message signs before the merging point to direct heavy vehicle drivers to move from the nearside lanes to far side lanes. As the model developed for another purpose, it was simple and not considered all variables. Furthermore, it was not validated and not implemented in traffic micro-simulations.

Rakha and Wang (2009) investigated the desired speed and acceleration of different vehicles. Different brands of vehicles from various manufactories were used for data collection and investigation. They included subcompact, compact, midsize, large, minivan, pickup, sport utility vehicles as well as heavy vehicles. The study explored the estimation of the Gipps (1981) CF model and showed that it overestimated vehicle speeds for heavy vehicles. The findings of this study could provide a good inspiration by showing that the capability of different vehicles could influence on their traffic behaviour characteristics. However, this study did not provide an applicable CF model for traffic simulations to consider the interactions between heavy vehicles and passenger cars.

Sarvi (2011) checked the time and space headways between two successive vehicles travelling at different speeds. Three different CF combinations were considered in this study: CF car, CF heavy vehicle, and heavy vehicle following car. It was shown that the headways were on average longer when heavy vehicles were following cars compared with when cars were following cars. It was shown that the headways in these combinations were smaller than when cars were following heavy vehicles. Notwithstanding the important outcomes, this study did not provide any specific CF model to replicate the findings.

Ossen and Hoogendoorn (2011) compared CF behaviour of heavy vehicles and passenger cars based on image processing of video recorded using a helicopter.

It was found that the speed of heavy vehicles was more regular compared with the speed of passenger cars. This phenomenon could be explained as the result of the greater weight of trucks compared with passenger cars which could result in less manoeuvrability of heavy vehicles. Also, it could be the result of the better adaptation and anticipation of heavy vehicle drivers due to having better sight distance and more driving experience relatively compared with passenger car drivers. This study considered the three aforementioned CF combinations and investigated the time headways between the vehicles. The results of this investigation showed that the time headways between the vehicles were varied amongst the combinations. Nevertheless, this study did not provide any model to capture the different CF behaviours of the vehicles in these combinations.

Two recent studies (Aghabayk, Sarvi, & Young, 2012, 2014) conducted detailed investigation into the impacts of heavy vehicles on driver's CF behaviours. Four combinations of heavy and passenger vehicles were considered for the assessment including

- heavy vehicle following passenger car (H-C),
- passenger car heavy vehicle (C-H),
- passenger car passenger car (C-C),
- heavy vehicle following heavy vehicle (H-H).

The studies showed that the headway between two heavy vehicles (H-H case) is the longest headway amongst the others and the space headway between two passenger cars (C-C case) is the shortest headway amongst the other CF combinations. The headways for the 'C-H' and 'H-C' cases are located between the 'H-H' and 'C-C' cases. It was also found that the headway in the 'C-H' case in longer than the 'H-C' case when the vehicle speed is less than 30 km/h. It will be shorter than 'H-C' case if the speed exceeds 30 km/h.

Furthermore, it was found that a heavy vehicle driver reacts to an action after 2 seconds when following another heavy vehicle. The reaction time would be 1/10 of second less if the driver follows a passenger car. It was concluded that a passenger car driver reacts to an action after 1.8 seconds when following another passenger car. This reaction time increased 1/10 of second when the passenger car driver follows a heavy vehicle.

In terms of acceleration analysis, it was showed that a heavy vehicle driver applied a lower acceleration and follows a preceding vehicle smoother than a passenger car driver. It was found that the acceleration sequence is 'H-H', 'H-C', 'C-H' and 'C-C'.

Furthermore, the analysis of the relation between relative speed and space headway between two successive vehicles involving in a CF process showed the differences amongst the four combinations. In addition, it was found that the explanatory variables that affect driver's CF behaviours are different based on the combinations. These studies showed the fundamental differences amongst the combinations but did not provide any specific model that could incorporate these different behaviours.

Aghabayk, Sarvi, Forouzideh, and Young (2013) developed a new artificial intelligence CF model which specifically considered heavy vehicles. The model used the local linear model tree (LOLIMOT) approach to predict the subject vehicle speed with the consideration of the vehicle type. Three different time slots of a data set obtained from a stretch of a freeway in USA (FHWA, 2005) were used in this study; two of them for training and testing purpose and another one for evaluating the proposed model.

The performance of the new model was evaluated by comparison of the results obtained from the model with the outcomes of two existing CF models. Gipps (1981) CF model and a neural network-based CF model were used for this purpose. Note that these models do not differentiate between heavy vehicles and passenger cars. The results showed that the new model could fit the real-world driver's CF behaviour better compared with the existing models. Although the study developed a new model that could incorporate the different CF behaviours of heavy vehicles and passenger cars, but it did not consider the impacts of heavy vehicles as the lead vehicles. Furthermore, this study did not implement the developed model to a traffic micro-simulation to quantify the effect of the developed model using variety of traffic scenarios.

In summary, the presented literature showed the impacts of existence of heavy vehicles in traffic stream on drivers' CF behaviours. This indicates that the existing models, in particular, the models used in traffic simulations may need to be revisited to be able to consider the detailed different CF behaviours of drivers in heterogeneous traffic.

6. Summary and Further Remarks

This study reviewed the existing microscopic CF models under the two major categories: classic and artificial intelligence models. Their concepts and properties were outlined along with providing some instances of their applications. It was pointed out that the classic models could provide some equations which are reasonable and thus make the models generally simpler to understand and use compared with the artificial intelligence models. However, most of the classic models assumed that drivers could detect even small changes and will react based on their precise detection which could not be realistic. Indeed, drivers react to the actions of the lead vehicle only when the perceived stimulus exceeds a certain threshold. One group of classic models (psychophysical models) could take this phenomenon into account by defining some perceptual thresholds. This characteristic of psychophysical models made this type of CF models more realistic and powerful but more difficult for calibration compared with the other classic models. Apart from the psychophysical models, fuzzy logic models as one group of the artificial intelligence models could consider the imprecise perception of drivers by defining a few fuzzy sets and rules. However, it would be generally difficult to determine these sets and rules. Neural networks based CF models were also reviewed in this paper. Although this type of models may replicate the real traffic reasonably well, there has had a common disagreement amongst some researchers that they are a black box.

This paper reviewed particularly the CF studies in which heavy vehicles were considered. It was found that some impacts of the presence of heavy vehicles in traffic stream on CF behaviours of drivers were acknowledged in the literature but with no implementation in traffic micro-simulations. Nevertheless, with attention to the increasing number of heavy vehicles and their impacts on traffic flow characteristics, further research may be required to revisit the existing models with specific consideration of heavy vehicles in traffic stream.

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