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Modelling lane-changing mechanisms on motorway weaving sections

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A motorway weaving section connects a pair of closely spaced entry- and exit-ramps, where intensive lane-changings of merging and diverging vehicles take place over a relatively short space. A detailed trajectory data reveal that a significant proportion of the lane changing at the weaving section exhibits group lane-changing behaviour, in the forms of a lane-changing platoon and simultaneous weaving behaviour. The acceptable gaps are different in group lane-changing and weaving, compared to a single isolated lane-changing. This paper proposes a random utility formulation with explicit representation of these different lane changing mechanisms. The model parameters are calibrated using Maximum Likelihood Estimation technique and individual vehicle trajectory data extracted from video recordings. There are significant differences in behavioural parameter values for lane changing mechanisms. In particular, the results suggest that the relative speed with respect to the current and target lane leaders have varying impacts on the gap acceptance behaviour.

Keywords: Lane changing; weaving section; group behaviour; leader effect; random utility maximization.

1. Introduction

In weaving sections, multiple traffic streams cross each other to reach their destination lanes along a relatively short section. In the UK, the typical length of a weaving section is between 2,000 – 3,000m (DMRB, 2006). In the US, the length is much shorter at between 150 – 762m (HCM, 2010). Traffic coming from the on-ramp merges onto the main-line traffic, while vehicles taking the next exit diverge to the exit lanes. The extensive lane-changes of the merging, diverging and through traffic are causes of increased congestion and high incident rates at weaving sections and lead to special operational problems to traffic managers (HCM, 2010; Jin, 2010; Skabardonis, 2002). Golob et al. (2004) reported that 37% of accidents in the weaving section occur in the middle lanes, out of which 23% are classified as sideswipes accidents and are attributed to high proportions of lane changing traffic. Skabardonis (2002) found that because of the complexity of vehicle interactions, operational problems may occur at weaving areas even when traffic volumes are well below capacity.

The complex movements also pose special challenges in modelling driving behaviour in weaving sections (Liu and Hyman, 2012) and lead to poor performances of the traffic microsimulation tools (Toledo and Katz, 2009). Consequently, in the study conducted by the Next Generation Simulation (NGSIM) program of US Federal Highways, driving behaviour models for weaving sections were identified as the weakness of the traffic simulation tools (Alexiadis et al., 2004). Better understanding lane-changing behaviour can, therefore, help in improving the fidelity of the traffic simulation tools, and thereby help in designing traffic management interventions to reduce accidents and associated traffic disruptions at weaving sections.

Wang et al. (1993) were the first to analyse the impact of individual vehicles' movements on the capacity of the weaving section. They found that the first 250ft (76m) downstream from the merge gore was the critical region with very high intensity of merging and diverging activities. Knoop et al. (2012) reported that the intensity of lane changing increases with the density of traffic in the origin lane as well as in the target lane. Analysing the NGSIM vehicle trajectory dataset, Bham (2006) identified that intensive lane changing movements (76% of the total lane changes) occur in the first 91m of the weaving section. Meanwhile, Al-Jameel (2011) studied the traffic characteristics in a typical urban weaving section in the UK and found that 70% of the lane changing occurs in the first 250m. Al-Kaisy et al. (1999) found that the locations of lane changes vary with the levels of congestion.

Wang et al. (2014) modelled the vehicle interactions during merging in a congested weaving section with a particular focus on yield behaviour. Sarvi et al. (2011) developed acceleration-deceleration models for weaving sections which demonstrate significant differences in behaviours of weaving and non-weaving traffic. The models presented in that study are however limited to acceleration-deceleration behaviours related to the merge rather than the lane changing the decision. Choudhury et al. (2009) looked at combined models of lane- changing and acceleration decisions in a merging context and reported significant differences in accepted gaps depending on the merging mechanism (normal, courtesy and forced). The study was however limited to the vehicles coming from the on-ramp and excluded other streams of traffic.

Our recent empirical analyses (Kusuma et al., 2014; 2015) reveal that 42% of the traffic in a weaving section make at least one lane change and there is significant occurrence of grouped lane-changing behaviour. For example, in 10.5% of the cases, two vehicles swap lanes with each other (weave) and in 5.6% of the cases, drivers change lanes following the preceding lane- changing vehicle (in a platoon). The lane changing characteristics are also found to vary for weaving and platoon lane changes. For example, the majority of the weaving lane changes have been observed to occur earlier on in a weaving section compared to the other lane changes.

The current study, therefore, aims to investigate the effects of the group behaviour in further detail and proposes a lane-changing modelling framework that explicitly accounts for the different lane changing mechanisms (i.e. isolated/solo, platoon and weaving movement). A random utility maximization approach is used in this regard and the model parameters are calibrated using the Maximum Likelihood Estimation (MLE) technique.

The rest of paper is organised as follows: Section 2 briefly explores the state-of-the-art lane-changing models with particular emphasis on random utility-based approaches. The proposed model specification is presented next followed by the data description and the estimation results. The summary of the findings and the directions for future research are presented in the end.

2. Literature Review and Contributions of the Present Paper

The existing literature on modelling lane-changing behaviour can be generally classified into three modelling approaches: rule-based simulation models, game theory models and random utility models of lane changing choices.

Gipps (1986) was among the first to develop a lane-change modelling framework based on a ruled based approach. This model captures the safety, necessity and desirability of the lane-changing movement. In rule-based models, the gap selection, acceleration and deceleration behaviour play significant roles during the lane-changing process (Zhang et al. 1998), as well as the lane-changing objectives. Gipps (1986) classified lane-changing objectives into mandatory lane-changing (MLC) where a vehicle changes lane in order to avoid an obstacle in front and discretionary lane-changing (DLC) where a vehicle changes lane in order to gain speed advantage. Liu (2010) further extended MLC as situations where a turning vehicle having to get into the correct turning lane, or a bus needing to get into/out of a bus layby. Most of the microscopic traffic simulation software adopt such rule-based models (e.g. SITRAS (Hidas, 2002), VISSIM (Fellendorf and Vortisch, 2010), PARAMICS (Sykes 2010), DRACULA (Liu et al., 2006). Wei et al. (2000) added a pre-emptive lane-changing scenario and identified gap acceptance as a critical factor in the lane-changing process. The lane-changing occurs if the driver accepts all three gaps: the lead gap at the current lane, the lead gap at target lane, and lag gap. Kesting et al. (2007) included a safety aspect, represented as the critical acceleration threshold, in lane-changing. Both driver aggressiveness (or politeness) factor and lane-changing location are found to affect the lane-changing rate, with lane-changing increasing significantly around the mandatory lane-changing location (i.e. at the end of a link or at an off-ramp). Such rule-based models are intuitive and easy to understand, but they have a number of inherent drawbacks. They are constrained by the behaviour rules specified a prior and the realism of these rules. For example, a model specifying an identical gap acceptance threshold for all drivers would lead to an unrealistic driving situation, since in reality, different drivers have different preferences on the gap acceptance which may also vary in different situations.

A game theory approach was first proposed by Kita (1999) where lane-changing is modelled as a two-person, non-zero-sum, non-cooperative game. In this approach, the objective of the game is to choose the safest action and the payoff is a function of the surrounding variables (i.e. gap to the lead vehicle, time to collision, etc.). Wang et al. (2005) and Hidas (2005) adopted the game theory approach to simulate the cooperative lane-changing and gap acceptance at the merge where the lag vehicle creates gaps and to facilitate the merging movement. Liu et al. (2007) improved the game theory approach by assuming that the vehicle aims to maintain their driving conditions and minimise the speed variations. Incorporating the cooperation behaviour and accident risk into the gap acceptance model, Chu et al. (2015) found that the mainline traffic density is the most important factor in the choice of merging mechanism. The study concluded that in higher traffic density, drivers tend to chase the gap in front the lead vehicle on the target lane (chase-merge), while in lower densities (< 40 veh/km/lane), drivers tend to select the following gap and yield before merging (yield-merge). However, these models are expected to perform well only in cooperative (as in weaving conditions) – they inherently do not have any mechanism for capturing the platoon lane changes and are somewhat redundant for solo lane changes. Given that the proposed model captures the full variation of individual driver decisions for different lane changing conditions (platoon and solo in addition to weaving), it is expected to outperform the game theory based models.

Yang and Koutsopoulos (1996) first introduced the random utility approach in the context of lane-changing. The approach provides greater flexibility in capturing the traffic interaction compared to both the rule-based and game-theory approaches. The lane-changing decision in this method is assumed to be affected by several factors such as driver impatient factor, relative speed, and appearance of the heavy vehicle. Adopting this approach, Ahmed et al. (1999) performed an extensive work on modelling lane-change decisions with discrete choice modelling approach. In this study, lane changing is modelled as the result of a two-step process: (1) lane selection and (2) gap acceptance. The probability of lane changing is the joint probability of target lane selection and gap acceptance and the parameters of these probability functions are estimated based on Maximum Likelihood Estimation method. Furthermore, Toledo (2003) and Toledo et al. (2005) advanced this idea by integrating MLC and DLC into a single framework and including all available lanes in the choice set respectively. The models, however, describe only the solo lane-changing behaviours and do not account for group behaviour that characterizes the weaving traffic.

The gap acceptance decision plays a key part in a driver's lane-changing behaviour. A substantial number of studies on gap acceptance behaviour have been performed with various structures and assumptions since the early 1960's. Herman and Weiss (1961) proposed that the gap acceptance follows an exponential distribution while Ashworth (1970) assumed a normal distribution. Daganzo (1981) proposed a probit model which acknowledges the correlations among the time-gap acceptance decisions of the same driver. In this case, the mean value of the gap acceptance model is known as the critical gap and is modelled as a random variable that is normally distributed across the population. The assumption of normal distribution in the study, however, raises a problem for extreme cases where it may yield negative values which prompted the use of a Log-normal distribution (Ahmed 1999). Since then, the Log-normal distribution has been used widely in the recent development of gap acceptance models, e.g. in Toledo et al. (2005), Farah et al. (2009), and Choudhury et al. (2010). Bham (2008) studied both time-gap and lag-gap acceptances under the congested and non-congested traffic. The study compared the performances between Gamma distributions and Log-normal distributions and found that Gamma distributions performed better. In the merging context, the critical gaps are found to be significantly different in congested conditions depending on if the driver is merging normally, expecting a courtesy yielding from the mainline driver or forcing in (Choudhury et al., 2007). The models are however developed for vehicles joining the mainstream from an on-ramp (Mandatory Lane Changing conditions) and do not involve any lane choice component. The behaviour of the other traffic streams (e.g. through and diverging traffic) and the complex interactions among the different streams are also not considered in that research.

The review of literature thus reveals a research gap in terms of capturing the effects of lane-changing mechanisms on weaving sections in the general lane-changing model structure. This can lead to unrealistic traffic characteristics, especially in weaving sections where there is a significant presence of group behaviours leading to wider variations in lane-changing mechanisms. This has been highlighted in the review conducted by the Next Generation Simulation (NGSIM) program of US Federal Highways, where driving behaviour models for weaving sections have been identified as weak points of the traffic simulation tools (Alexiadis et al., 2004). The current study aims to address this research gap by extending the state-of-the-art random utility-based models and by explicitly capturing the lane-changing mechanism classified based on the movement of the lead vehicle. A case study of traffic on a weaving section in a UK motorway (M1 J42-43) is used to calibrate the extended lane-changing model with respect to different type of leader vehicle movements.

3. Structure of the Lane-Changing Model for Weaving Traffic

3.1 Definitions of the different lane-changing mechanisms

Our earlier analysis of video recordings of lane-changes at a weaving section (Kusuma et al., 2014; 2015) identified several different types of lane-changing (LC) behaviour at weaving sections. These different lane-changing mechanisms are summarised below and they form the basis of our proposed new model structure presented later in this section.

Different to the driving behaviour on normal motorway sections where a driver selects a target lane and finds a suitable gap to change lanes, on weaving sections, the choices of the drivers can be significantly affected by the actions of their neighbouring drivers. For instance, if the leader vehicle is changing lanes in the same direction, the subject driver may be inclined to move as in a platoon and accept smaller lead gaps to complete the lane change manoeuvre. Similarly, the acceptable gaps may be different if there is a weaving manoeuvre as opposed to a solo lane-change which does not involve any marked interaction with the neighbouring drivers. The current research, therefore, extends the state-of-the-art lane-changing models by explicitly incorporating these different types of lane-changes in the model framework.

According to the definitions in HCM (2010), a platoon is a group of vehicles from the same traffic stream travelling together either voluntarily or involuntarily, while weaving is the crossing of two or more traffic streams in the same traffic direction in a short road length without any assistance of traffic control devices. With these definitions, this paper classifies lane-changing mechanisms as follows:

- Solo (s): this involves a single vehicle making a lane-changing, where its neighbouring vehicles (those in front on the same lane and those in its target lane) are nor making a lane-changing move at the same time (Fig 1a);
- Platoon (p): this represents a situation whereby the subject and its preceding vehicle from the same traffic stream change lanes together (as illustrated in Fig 1b). The preceding vehicle is termed as front vehicle in this paper;
- Weaving (w): this occurs if the subject vehicle and a vehicle from the adjacent traffic stream (on the left or right) cross each other at the same time (Fig 1c). In other words, the subject vehicle and the adjacent vehicle swap lanes to follow their preferred paths. The vehicle initiating the weaving is termed as the lead vehicle in this paper and the other one (which changes lane after seeing that the lead vehicle in the target lane has already indicated that he/she is changing lanes) is treated as the subject vehicle.

<***Figure 1*** Diagrammatic illustrations of the three-different lane-changing mechanisms>

According to Kusuma et al. (2014, 2015), the different lane-changing mechanisms yield differing sensitivities towards the positions and speeds of the front vehicle in the platoon and the lead vehicle in the target lane and lead to variations in the acceptable gaps for the lane change. It may be noted that, in very congested conditions, drivers on the mainline carriageway may slow down to assist the vehicles entering from the on-ramp or exiting to the off-ramp (Wang et al., 2006). This research deals with driving behaviour in moderately congested situations in correspond to HCM 2010 weaving section analysis algorithm. Moreover, the cooperative merging is beyond the scope of the current research.

3.2. A new lane-changing model structure for weaving traffic

Given the choice of the target lane and the lane changing mechanism, the subject driver may accept or reject an available gap. The acceptable gap can vary depending on the lane-changing mechanism. The acceptable gap is, however, unobserved in the data and only the final decisions of the driver: Change Left (CL), Change Right (CR) or No Change (NC) are observed. We propose a random utility modelling framework to model the lane-changing decisions at weaving. The model framework is illustrated in Fig. 2, where the observed decisions are shown in rectangles and the unobserved ones are shown in ovals. The proposed model structure is an extension of the generic freeway lane-changing model of Toledo et al. (2005). Different to Toledo et al. (2005), the new model structure has an added decision layer, the 'mechanism' (in Fig. 2), in which the different lane-changing mechanisms, including the two new mechanisms on platoon lane-changing and weaving, are explicitly represented.

An example of lane-changing structure for a subject driver in lane 3 of a 4 lanes road is shown in Fig 2. The driver first selects a target lane, which is the most preferred lane considering the traffic conditions and his/her path plan. The choice of the target lane indicates the preferred direction of a lane change. For example, for the subject driver in lane 3, lanes 2 and 1 are on the left-hand side and lane 4 is on the right- hand side (for UK driving regulations). If the target lane is the same as the current lane, the lane-changing is not required (the observed action is therefore NC). If the target lane is 1 or 2, the driver looks for suitable gaps on the left. If the target lane is lane 4, the driver seeks suitable gaps on the right. A lane change is observed when the driver finds an acceptable gap in the desired direction and moves to the left (CL) or to the right (CR). Otherwise, he/she stays in the current lane. It may be noted that the choice of target lane is unobserved in the trajectory data since the driver may or may not be successful in moving to the target lane.

<***Figure 2*** The lane-changing framework for a driver on lane 3 of a four-lane road.>

The driver looks for suitable gaps in the adjacent target lane in the direction of the target lane and executes a lane change if he/she finds an acceptable gap. The acceptable gap can be different depending on the lane-changing mechanism (i.e. solo, platoon or weaving). The observed actions of the front vehicle in the current lane and the lead vehicle in the target lane (see Fig 1) define the lane-changing mechanism. If the front vehicle is also changing lanes in the same direction, the subject driver has the option to execute (or not to) a platoon lane-change; whereas if the front vehicle in the current lane is not changing lanes in the same direction, but an adjacent vehicle in the target lane is making a change to the current lane, the subject driver has the option to execute (or not to) a weaving lane-change. The lane-changing mechanism is therefore explicitly represented in the model.

3.3. Model Formulations

In this section, we describe the detailed formulations of the target lane choice and gap acceptance model components. These are followed by the likelihood function for the trajectory that builds upon these model components.

3.3.1 The target lane choice model

We formulate the target lane choice as a utility-maximisation problem whereby a driver chooses the lane with the highest utility. The utility function of a driver (n) for choosing lane (l) at a specific time (t) can be written as follows:

$$U_n^l(t) = V_n^l(t) + \varepsilon_n^l(t)$$
$$= \beta^l X_n^l(t) + \alpha^l \vartheta_n + \varepsilon_n^l(t), l \in \{1,2,3, \dots, L\} \quad (1)$$

where:

$U_n^l(t)$: Target lane utility of driver n at time t;

$V_n^l(t)$: Systematic component of the target lane utility of driver n at time t;

$\varepsilon_n^l(t)$: Random error term associated with target lane l for driver n at time t;

$X_n^l(t)$: Vector of explanatory variables associated with driver n for lane l at time t;

β^l : Vector of estimated parameters associated with target lane l;

ϑ_n : Individual specific random error term (representing driver's aggressiveness) to account for unobserved driver characteristics, and is assumed to follow a normal distribution $\vartheta_n \sim N(0,1)$

α^l : Estimated parameters of individual specific random term ϑ_n for lane l;

L : Total number of available lanes in the section.

We assume that the trade-off between the Mandatory (MLC) and Discretionary lane changing (DLC) considerations is captured through the model variables and that the choice set of the driver includes all lanes over the road stretch (as in Toledo et al., 2005). The candidate variables affecting the choice of the target lane may include general traffic conditions (e.g. traffic density, average speed, orientation, etc. of each lane), surrounding vehicle attributes (e.g. relative speeds, types of surrounding vehicles, etc.), path-plan impact (e.g. whether or not the driver needs to take an exit or make a mandatory lane change in order to follow the path and if yes, what is the remaining distance to the exit), and driver characteristics (e.g. age, experience, stress level, aggressiveness, etc.). The driver characteristics are however generally unobserved directly from traffic surveillance (such as video recording or other sensor data) and are represented instead by statistical distributions (Choudhury, 2007; Toledo et al., 2005).

The choice model presumes that the random error term $\varepsilon_n^l(t)$ is independently and identically distributed (IID). Therefore, the probabilities of lane choice l conditional on individual specific random term ϑ_n can be written as:

$$P(l_n(t)|\vartheta_n) = \exp(V_n^l(t)|\vartheta_n) \,/\, \sum_{k=1}^{L} \exp(V_n^k(t)|\vartheta_n) \quad l,k \in \{1,2,3,\dots,L\} \tag{2}$$

3.3.2 The gap acceptance model

Gap acceptance is the second level of lane-changing decision-making process as shown in Fig.2. It is a result of interaction between the subject drivers and the traffic in the adjacent lane in the direction of the target lane. The interaction can be represented by variables such as relative speed between the subject vehicle and lead and/or lag vehicle at the target lane, the relative speed between the subject vehicle and the front vehicle in the current lane, types of vehicle, distance to exit etc.

The driver evaluates both lead and lag gaps against his/her acceptable gaps threshold, known as critical gaps. The lead and lag gaps are accepted if both are greater than the corresponding critical gaps. The critical gap of a driver is not constant or static; rather it can vary among drivers and for the same driver across observations depending on the surrounding conditions. In the existing utility-based models (e.g. Ahmed et al., 1996; Choudhury, 2007; Toledo and Katz, 2009; Toledo et al., 2005), critical gaps are assumed to follow Log-normal distributions (since the gaps have non-negative values) where explanatory variables represent the mean of the distribution. These models, however, do not address the effects of lane-changing mechanism on the critical gap values. We propose the following formulation, to explicitly incorporate the effects of lane-changing mechanisms in the choice process:

$$G_n^{cr,j,l,m}(t) = \exp\left(\beta^{j,m} X_n^{j,l,m}(t) + \alpha^{j,m}\, \vartheta_n + \varepsilon_n^{j,l,m}(t) \right);\ j \in \{lead, lag\}, m \in \{s, p, w\} \tag{3}$$

where;

$G_n^{cr,j,l,m}(t)$: Critical gap *j* in the direction of target lane *l* of driver *n* at time *t* associated with the lane-changing mechanism

$X_n^{j,l,m}(t)$: Vector of explanatory variables associated with driver *n* at time *t* looking for critical gap *j*, target lane *l* and lane-changing mechanism m

$\beta^{j,m}$: Vector of estimated parameters for critical gap *j* and lane-changing mechanism m

$\alpha^{j,m}$: Estimated parameters of individual-specific random effect ϑ_n for critical gap *j* and lane-changing mechanism *m*

$\varepsilon_n^{j,l,m}(t)$: Random error term associated with critical gap *j* and lane-changing mechanism *m* for driver *n* at time *t*, assumed to follow a normal distribution $N\left(0, (\sigma^{j,m})^2\right)$

Lane change at time t occurs if the driver accepts both the corresponding lead and the lag gaps. The probability of accepting available gaps in the direction of lane l at time t conditional on individual-specific random term ϑ_n can, therefore, be expressed as follows:

$$P(lc_n(t)|l_n(t), m_n(t), \vartheta_n)$$
$$= P\big((accept\ lead\ gap|l_n(t), m_n(t), \vartheta_n)\big)$$
$$* P\big((accept\ lag\ gap|l_n(t), m_n(t), \vartheta_n)\big)$$
$$= P\left(\left(G_n^{lead,l,m}\middle|l_n(t), m_n(t), \vartheta_n\right)\right) * P\left(\left(G_n^{lag,l,m}\middle|l_n(t), m_n(t), \vartheta_n\right)\right) \quad (4)$$

where:

$G_n^{lead,l,m}, G_n^{lag,l,m}$: Available lead and lag gaps at target lane l with mechanism m.

A Log-normal distribution of the gap acceptance probability can be written as follows:

$$P\big(G_n^{j,l,m}(t) \geq G_n^{cr,l,m}(t)\big|l_n(t), m_n(t), \vartheta_n\big)$$
$$= P\big[ln\big(G_n^{j,l,m}(t) \geq G_n^{cr,l,m}(t)\big|l_n(t), m_n(t), \vartheta_n\big)\big] \quad (5)$$
$$= \Phi\left[\frac{ln\big(G_n^{j,l,m}(t) - X_n^{j,l,m}\beta^{j,l,m} + \alpha^{j,m}\vartheta_n\big)}{\sigma^{j,m}}\right]$$

where:

$\Phi[\cdot]$: Cumulative standard normal distribution

3.3.3 The likelihood function

The model is estimated using detailed trajectory data that consists of second by second positions of all drivers in the section. The likelihood function is applied to estimate the parameters of the lane-changing model. As mentioned in the target lane section, the lane-changing model consists of two components: (1) target lane selection and (2) gap acceptance. The joint probability of observing a lane change at time t, $P\left(LC_{n\,n}^{l'}(t)\right)$ is a joint probability of choosing target lane l and accepting the available gap at the direction of lane l and can be expressed as follows:

$$P\left(LC_{n\,n}^{l'}(t)|\vartheta_n\right) = \sum_{l\in l'}\sum_{m}[P(l_n(t)|\vartheta_n)]\ [P(lc_n(t)|l_n(t), m_n(t), \vartheta_n)]$$

$$l' \in \{left, right, current\} \tag{6}$$

where $P\left(LC_{n\,n}^{l'}(t)\right)$ is the probability of lane change in direction l'.

$P(l_n(t)|.)$ and $P(lc_n(t)|.)$ are given by Equations 2 and 4 respectively. The trajectory data consists of a sequence of observations of the same driver over the study area. Assuming that the observations from different drivers are independent over time, the joint probability of the sequence observations can be specified as follows:

$$[P(LC_n^{l'}(1)|\vartheta_n)][P(LC_n^{l'}(2)|\vartheta_n)][P(LC_n^{l'}(3)|\vartheta_n)] \ldots [P(LC_n^{l'}(T_n)|\vartheta_n)] = \prod_{n=1}^{T_n}\sum_{l}\sum_{m}[P(l_n(t)|\vartheta_n)]\ [P(lc_n(t)|l_n(t), m_n(t), \vartheta_n)] \tag{4}$$

where T_n is the number of observed time period for each n^{th} driver (1, 2, 3, …., T_n)

Integrating Equation 7, the unconditional likelihood function (L_n) of the observed lane-changing behaviour over the distributions can be written as follows:

$$LC_n = \int_v \prod_{n=1}^{T_n}\sum_{l}\sum_{m}[P(l_n(t)|\vartheta_n)]\ f(\vartheta)\ d\vartheta \tag{5}$$

Note that $f(\vartheta)$ is a standard normal probability density function representing the distribution of aggressiveness of the drivers in the sample. Following the IID distribution of the error terms, the log-likelihood function for all N individual observation denotes:

$$L = \sum_{n=1}^{N} \ln LC_n \tag{9}$$

The maximum likelihood estimates of the model parameters are found by maximizing this function. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimisation algorithm is used for the maximization.

4. Model Estimation

The data used for the model estimation was collected in 2013 from the weaving section between Junction (J) 42-43 of the M1 motorway network in the UK (between Wakefield and Leeds). The level of congestion was moderate with a total traffic flow rate around 6586 vehicle/hour. The empirical observations and analysis were reported in Kusuma et al. (2014, 2015). In this section, we first summarise briefly the empirical findings. We then describe how the data extracted from the video recording are used for generating the variables of interest for the estimating the proposed model and present the model estimation results.

4.1 The Observation

The observation was made on a weekday afternoon (17:15-17:45) when the motorway traffic was moderately congested. The traffic movement analysis showing that, it indicates the traffic at the observation area is moderately congested with level of service C based on HCM 2010 algorithm. Fig. 3 shows a schematic drawing of the weaving section from J42 to J43. It is a five-lane dual-carriageway, with three lanes for through traffic (denoted as lanes 3, 4 and 5) and two auxiliary lanes (lanes 1 and 2) for merging and diverging traffic. The distance between J42-43 is 1,265m, which is slightly shorter than the 2,000m recommended by DMRB (2006) for a weaving section.

The video recording was made from an over-bridge located 620m downstream from J42 and was made in both directions. The first camera faced the traffic from J42 and recorded all five lanes of traffic. A second camera faced J43 and recorded the traffic between the overbridge and the exit ramp. The trajectory data was extracted using a semi-automated vehicle trajectory extractor application by Lee et al. (2008). The trajectory extraction software could however only process video recordings of 'front-views' of the cars. Therefore, the detailed trajectory data was available only for the first 320 m from J42 (between points M and N in Fig. 3). The data from the second camera (downstream of the over-bridge which provided 'back view' of the cars) was, however, useful for the creation of a local origin-destination (presented in Table 1) and for recording the total number of lane changes. This was done manually observing the videos rather than using any software.

The potential spatial inaccuracies in the data have been a concern in this case and in spite of best efforts, the data are likely to have errors due to the limitations of the video recording tool, pixel resolution, frame rate, camera vibration, camera synchronization and longitudinal and lateral angles. The trajectory data, therefore, was smoothed using the locally weighted regression technique and validated using the aggregate speed and flow information of the same time period obtained from the MIDAS database. The details of the extraction procedure are discussed in Kusuma et al. (2014, 2015). The final dataset includes 17,981 trajectory data points from 1,386 vehicles.

<***Figure 3*** The observation site >

The observed weaving section has two origin nodes: A from the main carriageway and B from J42 on-ramp, and two destination nodes: C to the exit at J43 and D continue on the motorway. The local origin-destination traffic volumes are obtained from the video survey data and listed in Table 1 below.

<Table 1 The 15-min origin-destination traffic volumes (vehicles) over the survey site>

Detailed descriptions of the extraction process and analysis of the extracted vehicle trajectory data have been presented in Kusuma et al. (2015). They found that the traffic speed in the observation area varies between 19m/sec and 38 m/sec, with mean value 26 m/sec (93.6 km/h). In this case, 19.5% of the traffic moves over the speed limit (112km/h). Moreover, the mean relative speed values between the subject and the current lane front vehicle and target lane lead and target lane lag vehicles are -0.76, -1.91 and 1.35 m/sec respectively. The distributions of the relative speeds and time gaps of the vehicles are presented in Fig. 4.

<***Figure 4*** Relative speed between the subject vehicle and (a) front vehicle on current lane, (b) lead vehicle* and (c) lag vehicle* at the target lane, and gap between the subject vehicle and (d) front vehicle, (e) lead vehicle* and (f) lag vehicle*.>

The accepted gap at target lane varies between 0.04[1] sec and 10.98 sec with a mean value 3.27 sec and median value 2.71 sec, while the accepted lag distributes between 0.59 sec

[1] The gaps in this study are measured when the observed vehicle initiates the lane-changing process (starts to change the direction). 0.04 sec is actually not the size of the gap during the actual execution. In this case, the observed lane-changing vehicles may expect that the gap size will increase and become larger during the execution of the lane change.

and 14.16 sec with mean value 5.23 sec and median value 4.15 sec. The accepted gap and lag distributions fit very well with a Log-normal distribution (as shown in Fig. 4 d, e, and f). The distributions are heavily skewed to the left implying that most of the drivers accept smaller lead and lag gaps during the lane-changing movement.

4.2 Lane-changing characteristics

Kusuma et al. (2015) examined the detailed individual vehicle trajectory data extracted from the first 320m of the weaving section (between location M and N on Fig. 3). We summarise below the key findings from their study on the observed lane-changing behaviour at the weaving section:

- 731 (53%) of the vehicles observed in the video data made at least one LC move. 458 of these lane changes were MLC movement - that is the lane change was essential either to exit from the motorway (O-D pair A-C, 185 vehicles) or to merge into the mainline traffic (O-D pair B-D, 273 vehicles). The remaining lane changing vehicles performed DLC movement.
- Most of the lane changing vehicles performed a single lane change (73.8% of total lane-changing traffic).
- The maximum number of lanes changed was three. This situation occurred for vehicles merging or diverging to or from the main traffic.
- Majority of the vehicles making more than one lane change performed staggered lane-changing strategy (18.6%) rather than direct one. For the staggered lane changes, the average driving time in transit lane was 2 sec.

- 95% of the total lane changes took place in the upstream section before the over-bridge. The remaining 5% took place after the over-bridge and is excluded from further analysis and modelling in the rest of the paper.

*<**Figure 5** Percentage distribution of vehicles in each lane at the start of the weaving section (location M in Fig. 3) and 320m downstream at location N >*

*<**Figure 6** Lane-changing frequencies by origin lane - destination lane>*

Fig. 5 shows the lateral distribution of all vehicles at the start and the end of the section (at locations M and N in Fig. 3 respectively), while Fig. 6 shows the lateral distribution pattern of lane changes. It can be seen that, whilst the lateral distributions of vehicles over the 320m section do not change significantly (Fig. 5), there are significantly different amount of lane-changing activities between lanes. Fig. 6 shows that Lanes 2 and 3 have the highest proportions of total lane changing, at 31% and 33.4% respectively, and the majority of which are making MLC (e.g. 26.8% from the merging Lane 2 to Lanes 3 – 5 on the main carriageway, and 31.9% from Lane 3 to the exit Lanes 1 and 2). Lane 4 also has a high proportion (at 18.8%) of lane changes. In total, 83.2% of the total lane changes are made by vehicles entering the weaving section in the middle three lanes, either as MLC to enter or exit the motorway, or as DLC perhaps to facilitate or be influenced by other lane changes nearby.

The vehicle trajectory dataset was also used to identify the location of lane changes and the different types of lane-changing behaviour. It is found that 76% of lane changes occur over the first 250m, as measured from the starting point of the weaving section (location *M* in Fig. 3). The trajectory data has revealed a significant amount of group lane changing behaviour (as either in a platoon or weaving). The proportions of different types of lane changes are: (1) solo: 76.6%; (2) platoon: 10.7%; and (3) weaving: 12.7%.

In total, 23.4% of the lane changing traffic are found to be involved in group behaviour (as either platoon or weaving), most of which are between Lane 3 and Lane 2. The substantial share of such group behaviour reinforces the need to incorporate the effect of different lane-changing mechanisms in lane-changing models and subsequently in traffic simulation models.

4.3. Model estimation results

The target lane and gap acceptance of the proposed lane change model are estimated jointly using a maximum likelihood approach as described in Section 3. The explanatory variables found to be statistically significant in the target lane model include lane characteristics (average speed and occupancy), relative speed with the vehicle in the front and path-plan variables (remaining distance to MLC point and the number of required lane changes) while those for the gap acceptance model are relative speed with the vehicle in the front and lead and lag vehicles in the target lane. 17,891 data points on individual vehicles' speeds and gaps extracted from video recordings (Kusuma et al., 2014), as well as the 1-minute averaged traffic speed and occupancy data are from the MIDAS loop detector, are used in the model estimation. Table 2 summarises the estimation results of the proposed lane-changing model. The description of the variables in the final model is presented in Table 3 along with the model components where they are used. The estimated model functions and their implications are presented below.

<Table 2 Lane-changing model estimation result>

<Table 3 Summary of Explanatory Variables>

4.3.1 Results for the target lane model

The probability of selecting a particular lane as the desired lane is affected by several attributes such as the average speed, occupancy and path-plan impact.

The lane specific constants denote that, with the other attributes being equal, a driver prefers Lane 3 the most as this lane provides ease of merging or diverging from the main traffic within and beyond the study area. Lane 2 is the next preferred lane. In contrast, all else being equal, the driver tends to avoid lane 5 which is further away from the entry and exit ramps and is the fastest lane.

As expected, the drivers prefer lanes with higher average speeds, faster front/lead vehicles and lower lane occupancies. The relative speed captures the interaction between the subject and lead vehicle. The positive sign of this attribute implies that the utility of a lane increases with the increase in relative speed to front/lead vehicle. It may be noted that the occupancy variable has been retained in the model in spite of the low t-stat which in this case is attributed to the small range of variation of the occupancy levels in the data. The coefficient has been retained because in an application scenario, the occupancy levels may vary more and the effect of this variable may not be trivial.

Rather than deterministically differentiating between DLC and MLC, the effects of path-plan are captured by the interaction of the required number of lane changes and the remaining distance to reach the MLC point. The magnitude of this effect amplifies as the vehicle approaches the MLC point (e.g. off-ramp location). This effect is represented by the negative power of remaining distance to the off-ramp $(\delta_n^{dist.exit} = -0.135)$. For example, if a driver needs to take the exit at 1m away from the off-ramp $\left(d_n^{exit}(t)=1\right)$, Lane 3 $\left(c_n(t)=1\right)$ has an additional disutility of 10.2*(1-0.135) units, Lane 4 $c_n(t) = 2)$has an additional disutility of 20.4*(1-0.135) units, etc. At 0.5m away from the off-ramp, the disutilities are 10.2*(0.5-0.135) units and 20.4* (0.5-0.135) units, respectively. This is shown schematically in an example in Fig. 7, where the disutility of being on the incorrect lane amplifies significantly as he/she approaches the end of weaving section. In terms of probabilities, this translates to the fact that the drivers have higher probabilities of making pre-emptive lane changes if they are multiple lanes away from the 'correct' lane.

*<**Figure 7** Impact of the distance to exit on the lane utility, for requiring one, two or three lane changes>*

The heterogeneity term $\vartheta_n(t)$captures the driver aggressiveness with respect to the target lane location either left or right of the current lane location. A positive sign on the left lane-changing direction implies that left lane changing drivers are more likely to choose a left lane over a right lane. The parameters are statistically insignificant though. However, they have been retained as they capture the correlation between the lane choice and the gap acceptance decisions of the same driver.

Giving the estimation result in Table 2, the target lane utility can be written as follows:

$$U_n^l(t) = \beta^l + 0.0174\,\overline{\mathrm{V}}_n^l(t) - 0.00185\,\mathrm{occ}_n^l(t) + 0.0487\,\Delta V_n^l(t) - 10.223 c_n(t)\left(d_n^{exit}(t)\right)^{-0.135} + \alpha^l \vartheta_n(t) + \varepsilon_n^l(t) \tag{10}$$

where:

β^l : Lane *l* specific constant

$\overline{\mathrm{V}}_n^l(t)$: Average speed at lane *l* of driver *n* at time *t* (m/sec)

occ_n^l : Lane *l* occupancy level of driver *n* at time *t*

$\Delta V_n^l(t)$: Relative speed between n^{th} driver and the leading vehicle at lane *l* at time *t*

$d_n^{exit}(t)$: Remaining distance to the mandatory lane-changing point of the n^{th} driver at time t, ∞ if no mandatory lane-changing is required.

$c_n(t)$: Number of lane changes required toward the target lane at time *t*

α^l : Estimated parameters of individual specific random effect ϑ_n for direction l' $\mathrm{l}' \in \{\mathrm{left}, \mathrm{right}\}$ depending on the orientation of target lane l with respect to the current lane.

The choice of the target lane indicates the direction of lane change (e.g. stay in the current lane, look for gaps in the right, look for gaps in the left) and the driver looks for acceptable gaps in that direction.

4.3.2 Results for the critical gap acceptance model

The gap acceptance is the second level of the lane change decision-making process. As described in Section 3, three different mechanisms of lane changes have been considered here: solo, platoon, and weaving. The explanatory variables modelled include the relative speeds with the front vehicle in the current lane and lead and lag vehicles in the target lane. The estimation results on the critical gaps are shown in Table 1 and are for each individual LC mechanisms as well as for all types of LC. The results indicate that the model constant terms differ significantly by lane-changing mechanism and that, all else being equal, the critical lead gap is the smallest for the platoon LC and the largest for weaving[2].

The critical lead gap of solo LC is found to be affected by both relative speeds with the lead vehicle in the target lane and front vehicle in the current lane. Meanwhile, the critical lead gap of the platoon lane-changing mechanism is affected by the relative speed with the front vehicle in the current lane only. On the other hand, the critical lead gap of the weaving lane-changing mechanism is affected by the relative speed with the lead vehicle in the target lane only. This is intuitive as for the platoon mechanisms; the front vehicle in the current lane has a more dominant role whereas for the weaving mechanism, the lead vehicle in the target lane has a more dominant role. The relative speeds have negative signs in the critical lead gaps associated with all lane-changing mechanisms denoting that the observed vehicle opts for a smaller gap if the front vehicle in the current lane or lead vehicle in the target lane is moving faster than the subject vehicle (i.e. gap opening up).

The coefficients of the individual-specific random terms and the standard deviations are also significantly different depending on the lane-changing mechanisms. An aggressive driver is defined as the one who requires a smaller critical gap all else being equal.

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[2] For weaving gap acceptance, the estimated model only applies to the instantaneous decision of the second vehicle (the one that changes lane after seeing that the lead vehicle in the target lane has already indicated that he/she is changing lanes)

Estimation results indicate that levels of aggressiveness have varied effects on the critical gaps depending on the lane-changing mechanism. The effect of aggressiveness is most (i.e. reduction in the critical gap is the largest) on weaving manoeuvres and least on platoon lane changes.

The lead critical gap functions for the three lane-changing mechanisms are presented below:

$$G_n^{cr,lead,l,s}(t) = exp\Big(-0.864 - 0.0204\ \Delta V_n^l(t) - 0.00730\ \Delta V_n^{cl}(t) - 1.440\ \vartheta_n^{lead,s}(t) + \varepsilon_n^{lead,s}(t)\Big) \quad (11)$$

$$\varepsilon_n^{lead,s}(t) \sim N\left(0, 0.150^2\right)$$

$$G_n^{cr,lead,l,p}(t) = exp\Big(-2.36 - 0.263\Delta V_n^{cl}(t) - 1.200\vartheta_n^{lead,p} + \varepsilon_n^{lead,p}(t)\Big), \quad (12)$$

$$\varepsilon_n^{lead,p}(t) \sim N(0, 1.69^2)$$

$$G_n^{cr,lead,l,w}(t) = \exp\Big(-0.539 - 0.127\Delta V_n^l(t) - 1.680\ \vartheta_n^{lead,w} + \varepsilon_n^{lead,w}(t)\Big), \quad (13)$$

$$\varepsilon_n^{lead,w}(t) \sim N(0, 0.410^2)$$

where:

$G_n^{cr,lead,l,m}(t)$: Critical lead gap at the direction of target lane *l* of the n^{th} driver at time *t* for lane-changing mechanism m, where m; Solo (*s*), Platoon (*p*) or Weaving (*w*)

$\Delta V_n^l(t)$: Relative speed between the n^{th} driver and the lead vehicle in the direction of the target lane l at time t

$\Delta V_n^{cl}(t)$: Relative speed between the n^{th} driver and the front vehicle at current lane *l* at time *t*

It may be noted that the gap-acceptance decision has already been made at time t. The relative speed for the platoon gap acceptance thus refers to the speed difference with the front vehicle at time t when both vehicles are in the same lane and the subject driver knows from the indicator that the vehicle in the front is changing lanes in the same direction. Similarly, for weaving gap acceptance, the relative speed refers to the speed difference with the lead vehicle in the target lane at time t who has indicated that he/she is changing lanes.

The variations of median lead critical gaps and observed gaps with different relative speeds of the front and lead vehicles are presented in Fig. 8 respectively.

Due to the limited availability of the observed data it was not possible to conduct any independent validation exercise. However, following the general guidance on simulation model and data validation methods (e.g. Antoniou et al., 2014; Hollander and Liu, 2007), we also compared the estimated critical lead gap variations with the corresponding observed gaps for the three lane-changing mechanisms as a function of relative speed. The analysis uses a nonlinear regression to capture the relationship between the observed accepted gap (dependent variable) and relative speed (explanatory variable) for the fitted trajectory dataset. Similar to the critical gaps, the regression results show that the accepted lead gaps increase with the relative speed between the subject vehicle and front/lead vehicles. Further, the critical lead gaps are always found to be slightly smaller compared to the observed accepted leads gaps (as expected) which validates the results.

The analysis of critical gap confirms that the critical gap is slightly increased with relative speed between the subject and both current lane front vehicle and target lane lead vehicles. The platoon lane-changing mechanism, which tends to be the simplest lane-changing movement, has the lowest critical gap compared to solo and weaving lane-changing mechanisms. The driver in this mechanism is relatively relaxes and follow the movement of front vehicle, who takes the role to initiate an interaction for creating space with the target lane traffic.

<***Figure 8*** *Variation of median lead critical gaps (predicted) and accepted gaps (observed) in as a function of relative speed*>

Asymptotic t-tests have been used to test the statistical differences in the coefficients (as suggested by Ben-Akiva and Lerman (1985). The test results indicate rejection of the null hypotheses at 5% level of significance. The differences in the specification of the critical lag gap depending on the lane-changing mechanism, however, revealed statistically insignificant differences (which is intuitive) and therefore a common lag gap acceptance model has been retained.

The results indicate that the relative speed coefficient has a positive sign indicating that the critical lag gap of the lane-changing vehicle is larger if the lag vehicle in the target lane is moving faster (i.e. gap closing). Similar to the critical lead gaps, the critical gaps are found to be smaller for aggressive drivers. The estimated critical lag gap function can is as follows:

$$G_n^{cr,lag,l}(t) = exp\left(0.421 + 0.015\Delta Vtar_n^{lag,l}(t) - 2.42\vartheta_n^{lag} + \varepsilon_n^{lag}(t)\right) \tag{14}$$

where:

$\mathrm{G_n^{cr,lag,l}(t)}$: Lag critical gap at target lane *l* of driver *n* at time *t*

$\mathrm{\Delta V_n^l(t)}$: Relative speed between the n^{th} driver and the lag vehicle in the direction of the target lane *l* at time *t*

$\varepsilon_n^{lag}(t) \sim N\left(0, 0.872^2\right)$

***<Figure 9** Variation of median lag critical gaps (predicted) and accepted gaps (observed) as a function of relative speed>*

The individual-specific constant of the critical lag gap indicates that it has slightly larger value compared to the critical lead gaps of all lane-changing mechanisms. That is to say that the driver is more alert when accepting the lag due to the difficulty in interpreting the lag vehicle behaviour (i.e. observe through the mirror) rather than the downstream traffic movement. This agrees with the findings of Bham (2008) for non-congested situations.

Similar to the lead gaps, for validation, we compared the estimated critical lag gap variations with the corresponding accepted lag gaps (observed) as a function of relative speed. The analysis uses a nonlinear regression to capture the relationship between the observed accepted lag gap (dependent variable) and relative speed (explanatory variable) for the given fitted trajectory vehicle dataset. Similar to the lead gaps, the regression results show that the observed accepted lag gaps increase with the relative speeds between the subject vehicle and lag vehicles and the critical lag gaps are always be slightly smaller compared to the observed lag accepted gaps (which validates the results).

4.4. Model comparison

The proposed model is compared with a model that ignores the effect of lane-changing mechanisms in the model structure (as in Toledo et al. 2005) that has been re-estimated using the M1 data. This model assumes same critical gap functions irrespective of lane-changing mechanisms and is referred as the ‘Restricted’ model. The proposed extended model with different model parameters for solo, weaving and platoon lane changes is referred as the ‘Unrestricted’ model.

The summary statistics of the estimation results for the two models are presented in

<Table 4. The model with explicit lane-changing mechanisms has larger values in terms of both Akaike Information Criteria (AIC) and Adjusted Rho-Square (ρ^2) indicating an improvement in the fitness of the proposed model, even after discounting for the larger number of parameters.

<Table 4 Model comparison>

Furthermore, the improvement in the goodness of fit is also tested using Likelihood Ratio Tests:

$$\begin{aligned} \textit{Likelihood Ratio Test value} &= 2 * \left(L(\beta^{*,res}) - L(\beta^{*,unres})\right) \\ &= 63.08 > \chi^2_8(15.51) \end{aligned} \quad (15)$$

This confirms that the inclusion of the lane-changing mechanisms in the decision framework results in a statistically significant improvement in the goodness-of-fit even after discounting for the increase in the number of parameters. These findings are in line with the asymptotic t-test results (Section 4.3.2), which denote that the parameters for platoon and weaving are statistically different from those of solo lane changes.

5. Conclusions

This paper extends the state-of-the-art random utility-based lane-changing model to explicitly incorporate the effect of the lane-changing mechanism (platoon, weaving and solo) in the modelling framework. The model parameters are estimated using vehicle trajectory data collected from a weaving section on the M1 motorway network between J42-43 in the UK. The estimation results indicate significant differences in parameters as well as influencing variables among the three types of lane-changing mechanisms. This is supported by statistically significant improvements in the goodness-of-fit results as well as asymptotic t-tests.

The practical implications of the research are highlighted below:

1. Safety implications: The model estimates provide critical insights that can be used to increase safety in weaving sections. For example, parameter values indicate that

all else being equal, platooned lane-changing involves smaller gap and there can be significant spread in critical gaps of weaving lane changes. Interventions like advising drivers to keep larger headways in weaving sections can, therefore, play a significant role in making the weaving sections safer.

2. Efficiency implications: The model estimates also indicate that platoon and weaving drivers are more sensitive to relative speed changes and increase their critical gaps significantly with negative relative speed. Advice/interventions (such as the variable speed limits) to equalise vehicle speeds would, therefore, reduce the critical gap and improve lane-changing efficiency. Estimates also validate that if multiple lane changes are required, a vehicle is more likely to occur at the beginning of a weaving area. Interventions to separate lane-changing for merging from lane-changing for diverging would minimise the intensity of lane-changing at the beginning of weaving area and spread lane-changing across the whole weaving area. This can improve safety as well as the traffic performance of the weaving section.
3. Potential to lead to better microsimulation tools: The current models are yet to be validated in any microsimulation tool. However, the improvements in the goodness-of-fit statistics provide strong indications of the potential to improve the weaving behaviour in microsimulation tools which has been identified as a weak point of the traffic simulation tools (Alexiadis et al. 2004).

The research, however, has several limitations. First of all, the data used for the research includes trajectory data extracted from video recordings, which though widely used, have known limitations such as the possibilities of spatial measurement errors and absence of driver characteristics and information about lane-changing indicators. The quality of the models would certainly be improved with better data. More data, possibly from other locations, would have also enabled us to perform out-of-sample validation which we recommend as an area of further research. Secondly, the proposed models are estimated using data collected from moderately congested traffic conditions. Though this provided the opportunity to observe higher shares of platoon and weaving mechanisms, it lacked observations on other mechanisms, as such courtesy and forced lane changes. The results, therefore, are therefore generalized since they may not be directly applicable to congested or over saturated situations. It will be interesting to test the transferability of the estimation results in other weaving sections and other congestion levels in future research. Further, the current models are yet to be validated in any microsimulation tool to investigate the improvements in the aggregate level predictions resulted by the improvements in the goodness-of-fit of the model parameters. Another potential direction of extension can be to investigate the effect of the lane-changing mechanism on acceleration behaviour.

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References

Ahmed, K., 1999. Modeling drivers' acceleration and lane changing behavior. PhD Thesis. Massachusetts Institute of Technology, USA. Massachusetts Institute of Technology, USA.

Ahmed, K., Ben-Akiva, M., Koutsopoulos, H.N., Mishalani, R.G., 1996. Models of freeway lane changing and gap acceptance behavior., in: Lesort, J.-B. (Ed.), Proceedings of the 13th International Symposium on the Theory of Traffic Flow and Transportation. Oxford, UK, pp. 501–515.

Al-Jameel, H., 2011. Developing a simulation model to evaluate the capacity of weaving section. PhD Thesis. University of Salford, UK.

Al-Kaisy, A.F., Stewart, J.A., Aerde, M. Van, 1999. Microscopic simulation of lane changing behaviour at freeway weaving sections. Canadian Journal of Civil Engineering 26(6), 840–851.

Alexiadis, V., Gettman, D., Hranac, R., 2004. NGSIM- Task D: Identification and prioritization of core algorithm categories. Federal Highway Administration. FHWA-HOP-06-008.

Antoniou, C., Casas, J., Koutsopoulos, H. and Liu, R (2014) *Traffic Simulation and Data Validation Methods and Application, Chapter 7 – Validation.* (Eds: Daamen, W., Buisson, C and Hoogendoorn, S.P.). CRC Press Taylor & Francis Group.

Ashworth, R., 1970. The analysis and interpretation of gap acceptance data. Transportation Science 4(3), 270–280.

Ben-Akiva, M., Lerman, S.R., 1985. Discrete choice analysis: Theory and application to travel demand. MIT Press, Cambridge, Massachusetts, USA.

Bham, G.H., 2008. Analyzing microscopic behavior: driver mandatory lane change behaviour on a multilane freeway. Missouri S&T, Center for Infrastructure Engineering Studies. UTC R157.

Bham, G.H., 2006. Intensity of lane changing at freeway weave section, in: Wang, K.C.P., Smith, B.L., Uzarski, D.R., Wong, S.C. (Eds.), 9th International Conference on Applications of Advance Technology in Transportation. American Institute of Physics, Chicago, Illinois, USA, pp. 310–318.

Choudhury, C., Ben-Akiva, M., Toledo, T., Rao, A., Lee, G., 2007. Modeling statedependence in lane-changing behavior, in: Allsop, R.E., Benjamin, G.H., Bell, M.G.H. (Eds.), 17th International Symposium on Transportation and Traffic Theory, London, UK.

Choudhury, C.F., 2007. Modeling driving decisions with latent plans. PhD Thesis. Massachusetts Institute of Technology, USA.

Choudhury, C., Ramanujam, V., & Ben-Akiva, M. (2009). Modeling acceleration decisions for freeway merges. Transportation Research Record: Journal of the Transportation Research Board, (2124), 45-57.

Choudhury, C.F., Ben-Akiva, M., Abou-Zeid, M., 2010. Dynamic latent plan models. Journal of Choice Modelling 3(2), 50–70.

Chu, T.D., Miwa, T., Morikawa, T., 2015. Gap acceptance on urban expressway merging sections: an application of inverse time to collision, in: TRB 94th Annual Meeting Compedium of Papers.

Cleveland, W.S., Devlin, S.J., 1988. Locally weighted regression : An approach to regression analysis by local fitting. Journal of the American Statistical Association 83(403), 596–610.

Daganzo, C.F., 1981. Estimation of gap acceptance parameters within and across the population from direct roadside observation. Transportation Research Part B: Methodological 15(1), 1–15.

DMRB, 2006. Design Manual for Roads and Bridges. Highway Agency, UK.

Farah, H., Bekhor, S., Polus, A., Toledo, T., 2009. A passing gap acceptance model for two-lane rural highways. Transportmetrica 5(3), 159–172.

Fellendorf, M. and Vortisch P. (2010). Microscopic traffic flow simulator VISSIM, in: Barceló, J. (Ed.), Fundamentals of Traffic Simulation, Chapter 8, International Series in Operations Research & Management Science. Springer New York, pp. 295–322.

Gipps, P.G., 1986. A model for the structure of lane-changing decisions. Transportation Research Part B: Methodological 20(5), 63–94.

Golob, T.F., Recker, W.W., Alvarez, V.M., 2004. Safety aspects of freeway weaving sections. Transportation Research Part A: Policy and Practice. 38(1), 35–51.

HCM, 2010. Highway Capacity Manual 2010. Transportation Research Board, USA.

HCM, 2000. Highway Capacity Manual 2000. Transportation Research Board, USA.

Herman, R., Weiss, G., 1961. Comments on the highway-crossing problem. Operation Research 9(6), 828–840.

Hidas, P., 2005. Modelling vehicle interactions in microscopic simulation of merging and weaving. Transportation Research Part C: Emerging Technologies 13(1), 37–62.

Hidas, P., 2002. Modelling lane changing and merging in microscopic traffic simulation. Transportation Research Part C: Emerging Technologies 10(5), 351–371.

Hollander, Y. and Liu, R. (2008) The principles of calibrating traffic microsimulation models. Transportation, 35(3), 347-362.

Jin, W.-L., 2010. Macroscopic characteristics of lane-changing traffic. Transportation Research Record: Journal of the Transportation Research Board 2188, 55–63.

Kesting, A., Treiber, M., Helbing, D., 2007. General lane-changing model MOBIL for car-following models. Transportation Research Record: Journal of the Transportation Research Board 1999, 86–94.

Kita, H., 1999. A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. Transportation Research Part A: Policy and Practice 33(3), 305–312.

Knoop, V.L., Hoogendoorn, S.P., Shiomi, Y., Buisson, C., 2012. Quantifying the number of lane changes in traffic. Transportation Research Record: Journal of the Transportation Research Board 2278, 31–41.

Kusuma A; Liu R; Choudhury C; Montgomery F (2014) Analysis of the driving behaviour at weaving section using multiple traffic surveillance data, Transportation Research Procedia, 3, pp.51-59

Kusuma, A., Liu, R., Choudhury, C.F., Montgomery, F., 2015. Lane-changing characteristics at weaving section, in: TRB 94th Annual Meeting Compedium of Papers.

Lee, T., Polak, J.W., Bell, M.G.H., 2008. Trajectory Extractor Version 1.0. Centre for Transport Studies. Imperial College, London, UK.

Liu, H.X., Xin, W., Adam, Z., Ban, J., 2007. A game theoretical approach for modelling merging and yielding behaviour at freeway on-ramp sections. Elsevier, London 197–211.

Liu, R., 2010. Traffic simulation with DRACULA, in: Barceló, J. (Ed.), Fundamentals of Traffic Simulation, Chapter 8, International Series in Operations Research & Management Science. Springer New York, pp. 295–322.

Liu, R., Hyman, G., 2012. Modelling motorway merge: The current practice in the UK and towards establishing general principles. Transport Policy 24, 199–210.

Liu, R., van Vliet, D. and Watling, D. (2006) Microsimulation models incorporating both demand and supply dynamics. Transportation Research, 40A, 125-150.

Sarvi, M., Ejtemai, O., Zavabeti, A., 2011. Modelling freeway weaving manoeuvre, in: 34th Australian Transport Research Forum, 28-30 Sept. Adelaide, Australia.

Skabardonis, A., 2002. Simulation of freeway weaving areas. Transportation Research Record: Journal of the Transportation Research Board 1802, 115–124.

Syles, P., 2010. Traffic simulation with Paramics, in: Barceló, J. (Ed.), Fundamentals of Traffic Simulation, Chapter 8, International Series in Operations Research & Management Science. Springer New York, pp. 131–172.

Toledo, T., 2003. Integrated driving behavior modeling. PhD Thesis. Massachusttes Insitute of Technology, USA.

Toledo, T., Choudhury, C., Ben-Akiva, M., 2005. Lane-changing model with explicit target lane choice. Transportation Research Record: Journal of the Transportation Research Board 1934, 157–165.

Toledo, T., Katz, R., 2009. State dependence in lane-changing models. Transportation Research Record: Journal of the Transportation Research Board 2124, 81–88.

Wan, X., Jin, P.J., Yang, F., Ran, B., 2014. Modeling vehicle interactions during freeway ramp merging in congested weaving section. Transportation Research Record: Journal of the Transportation Research Board 2421, 83–92.

Wang, J., 2006. A merging model for motorway traffic. PhD Thesis. University of Leeds, UK.

Wang, J., Liu, R., Montgomery, F., 2005. A simulation model for motorway merging behaviour, in: Mahmassani, H. (Ed.), Transportation and Traffic Theory: Flow, Dynamics and Human Interaction (ISTTT). Elsevier Ltd, pp. 281–302.

Wang, M., Cassidy, M., Chan, P., May, A., 1993. Evaluating the capacity of freeway weaving sections. Journal of Transportation Engineering 119(3), 360–384.

Wang, X., Luo, Y., Qiu, T.Z., Yan, X., 2014. Capacity estimation for weaving segments using a lane changing model. Transportation Research Record: Journal of the Transportation Research Board 2461, 94–102.

Wei, H., Lee, J., Li, Q., Li, C., 2000. Observation-based lane-vehicle assignment hierarchy: Microscopic simulation on urban street network. Transportation Research Record: Journal of the Transportation Research Board 1710, 96–103.

Yang, Q., Koutsopoulos, H., 1996. A microscopic traffic simulator for evaluation of dynamic traffic management systems. Transportation Research Part C: Emerging Technologies 4(3), 113–129.

Zhang, Y., Owen, L., Clark, J., 1998. Multiregime approach for microscopic traffic simulation. Transportation Research Record: Journal of the Transportation Research Board 1644, 103–114.