# MODELLING THE HEAVY VEHICLE DRIVERS' LANE CHANGING DECISION UNDER HEAVY TRAFFIC CONDITIONS

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## ABSTRACT

Lane changing manoeuvres of heavy vehicles have significant influence on traffic flow characteristics of the surrounding vehicles. This influence is due to the physical effects that the heavy vehicles impose on surrounding traffic. This paper presents an exclusive fuzzy logic lane changing decision model for heavy vehicle drivers on freeways. The trajectory data which is applied in this study is under heavy traffic conditions. Then, the efficiency of the calibrated lane changing decision model is examined. The validation results show that the new fuzzy logic lane changing decision model could closely replicate the observed lane changing decisions of the heavy vehicle drivers.

***Keywords*:** Lane changing decision; Heavy vehicles; Heavy traffic conditions.

## 1. INTRODUCTION

Lane changing manoeuvres of heavy vehicles have significant influence on traffic flow characteristics of the surrounding vehicles due to the physical effects that the heavy vehicles impose on surrounding traffic (Moridpour et al. 2008; 2009). These effects are the result of heavy vehicles' length, size, weight and the limitations in their manoeuvrability (Uddin and Ardekani, 2002; Al-Kaisy and Hall, 2003; Al-Kaisy et al., 2005). Considering the specific physical and operational characteristics of heavy vehicles, understanding the lane changing behaviour of heavy vehicle drivers is very important. However, the previous lane changing models are mainly associated with passenger car drivers and the lane changing behaviour of heavy vehicles has received little attention.

Several approaches have been applied to model the drivers' lane changing decision. The conventional lane changing decision models are mainly based on mathematical equations and crisp magnitudes to model drivers' lane changing decision (Das and Bowles 1999; Das et al. 1999). However, in real world the drivers' make their driving decisions based on their imprecise perceptions of the surrounding traffic. To overcome this problem, several approaches have recently become popular such as fuzzy logic. Fuzzy logic provides the opportunity to introduce a quantifiable degree of uncertainty into the modelling procedure to reflect the natural or subjective perception of the real variables (Wu et al. 2000).

This paper presents an exclusive fuzzy logic lane changing decision model for heavy vehicle drivers on freeways. The freeway trajectory data which is used in this study is under heavy traffic conditions. The trajectory data regarding a number of heavy vehicles which performed lane changing manoeuvre as well as a number of heavy vehicles which continued their path without lane changing are used to develop the lane changing decision model for heavy vehicle drivers.

This paper begins by reviewing the literature on fuzzy logic lane changing decision models and identifies the main limitation of the existing lane changing models. The freeway trajectory data used in this study is described in the following section. Then, the structure of the fuzzy logic lane changing decision model is presented in detail. It is followed by presenting and interpreting the estimated results. The final section summarizes the findings and conclusions of the paper and identifies directions for future research.

## 2. LITERATURE REVIEW

The traditional lane changing decision models mainly use mathematical equations and conventional logic rules to model the drivers' lane changing decisions. These models do not consider the inconsistencies and uncertainties of drivers' perception and decisions (McDonald et al. 1997). Traditional lane changing decision models are based on crisp magnitudes of variables (Das and Bowles 1999; Das et al. 1999). This is in contrast to the real world in which, drivers make their decisions based on their imprecise perceptions of the surrounding traffic (Ma 2004). In recent years, several approaches have become popular to solve the problems of traditional models. Some of these are the approaches which are based on Artificial Intelligence (AI). One type of AI is fuzzy logic model. Fuzzy logic models allow defining uncertainty in the model and therefore, reflect the natural or subjective perception of real variables.

Das et al. (1999) proposed a new microscopic simulation methodology based on fuzzy IF-THEN rules and called the software package as Autonomous Agent SIMulation Package (AASIM). The major motivation of using a fuzzy knowledge based approach to model drivers' decisions is that fuzzy models provide an effective means to change highly nonlinear systems into IF-THEN rules. In addition, fuzzy logic is well equipped to handle uncertainties which are inherent in real world traffic situations. In their microscopic simulation model, they assume that the lane changing manoeuvre occurs when the vehicle is not in a car following situation. They classified the lane changing manoeuvres as Mandatory Lane Changes (MLC) and Discretionary Lane Changes (DLC). MLC happen when a driver is forced to leave the current lane for instance when merging onto the freeway from an on-ramp or taking an exit off-ramp. DLC is performed when the driver is not satisfied with the driving situation in the current lane and wishes to gain some speed advantage for instance when the driver is obstructed by a slow moving vehicle. To decide when MLC happen in the microscopic traffic simulation, the MLC fuzzy rules consider the distance to the approaching exit or merge point and the number of lane changing manoeuvres which are required for the driver to stay in the appropriate lane. When multiple lane changes are required, the probability of making a decision to perform lane changing manoeuvre increases. The DLC rules of AASIM reflect a binary decision (lane changing or not) which is based on two parameters. These two parameters include:

driver's speed satisfaction level which is the drivers' recent speed history, and the level of congestion in the left or right adjacent lanes.

In AASIM, when drivers decide to perform a lane changing manoeuvre, finding a gap is the next stage. The fuzzy rules are based on car following data and also the adjacent gaps and surrounding vehicles' speeds in the target lane. To find a gap of sufficient size, an acceleration value is calculated which is different from that generated by normal car following rules. If there is an acceptable size of gap in the target lane, the gap finding rules enable the vehicle to either increase or decrease the speed to become closer to the gap. At the same time, the gap finding rules consider the safe headway to the front vehicle in the current lane. The last stage in AASIM lane changing decision model is setting the gap acceptance rules. These rules look for the gaps and speeds of the lead and lag vehicles in the target lane and the distance to the next exit or lane merge (infinite for DLC).

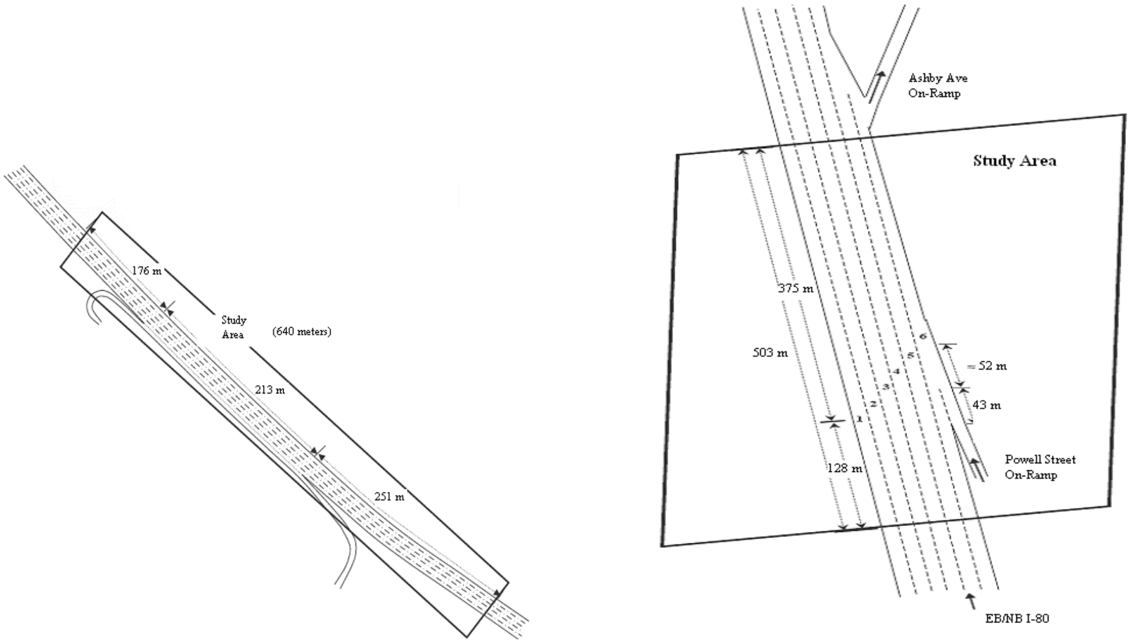
McDonald et al. (1997) Brackstone et al. (1998) and Wu et al. (2000) developed a fuzzy logic motorway simulation model (FLOWSIM) and established fuzzy sets and systems for the model. To model the lane changing decision, they classified the lane changing manoeuvres into two categories: lane changes to the near-side lane and lane changes to the off-side lane. Lane changes to the near-side are mainly performed to prevent disturbing the fast moving vehicles which approach from the rear. Lane changes to the off-side lane are mainly performed with the aim of gaining some speed advantages. Their near-side lane changing decision model uses two variables: pressure from the rear and gap satisfaction in the near-side lane. The pressure from the rear is the time headway of the rear vehicle. The gap satisfaction is the period of time during which it would be possible for the subject vehicle driver to stay in the selected gap in the near-side lane, without reducing speed. To establish the off-side lane changing decision model, they defined two variables: overtaking benefit and opportunity. The overtaking benefit is the speed advantage when an off-side lane changing manoeuvre is performed. The opportunity reflects the safety and comfort of the lane changing manoeuvre, which is measured by the time headway to the first lag vehicle in the off-side lane.

The above mentioned lane changing decision models are mainly associated with passenger car drivers and the lane changing decision of heavy vehicle drivers is neglected. Therefore, developing a specific lane changing decision model for heavy vehicle drivers is an important priority in developing the lane changing models.

## 3. TRAJECTORY DATASET

The trajectory data used in this study was provided for two freeways in California: Hollywood Freeway (US-101) and Berkeley Highway (I-80). The schematic illustration of the two freeway sections is shown in Figure 1.

The first section is on US-101 (Figure 1a). This section is 640 meters long and has five main lanes and one auxiliary lane. The section includes one on-ramp and one off-ramp exit and there are no lane restrictions applying to heavy vehicles (FHWA 2005). The data was collected from 7:50 to 8:35 AM with a video capture rate of 10 frames per second. The section of I-80 (Figure 1b) is 503 meters long and comprises five main lanes with one auxiliary lane. There is one on-ramp in this section and one exit off-ramp downstream of the section (FHWA 2005). There are no lane restrictions for heavy vehicles in this section. The data were collected from 4:00 to 4:15 PM and 5:00 to 5:30 PM using a video capture rate of 10 frames per second.




(a) The section of US-101. (b) The section of I-80.

Figure 1: Schematic illustration of lane configuration for the two freeway sections.

The dataset was provided in clear weather, good visibility, and dry pavement conditions. The dataset has classified vehicles as automobiles, heavy vehicles and motorcycles. Table 1 shows the traffic composition details and the traffic flow parameters for each study area.

Table 1: The distribution of different vehicle types in each freeway section.

| Site Name | Automobile Number (%) | Heavy Vehicles Number (%) | Motorcycle Number (%) | Flow (veh/hr) | Speed (km/hr) | Density (veh/km) | Level Of Service (LOS) |
|---|---|---|---|---|---|---|---|
| US-101 | 5919 (97.0) | 137 (2.2) | 45 (0.7) | 7603 | 35.2 | 216 | E |
| I-80 | 5408 (95.2) | 215 (3.8) | 55 (1.0) | 7493 | 23.5 | 319 | E |
| Total | 11327(96.2) | 352 (3.0) | 100 (0.8) | 7548 | 29.4 | 268 | E |

To develop an accurate lane changing decision model for heavy vehicle drivers, the traffic characteristics of the surrounding vehicles should be considered in two different driving regimes: while a lane changing manoeuvre occurs and when the heavy vehicle drivers continue their path without performing the lane changing manoeuvre. Therefore, over the time period that the data was captured, 21 heavy vehicle lane changing manoeuvres were selected to analyse in this study. In addition, a similar number of heavy vehicles with no lane changing manoeuvre were selected for model development. To ensure a valid model development, the surrounding traffic characteristics of the selected heavy vehicles with no lane changing manoeuvre were close to the surrounding traffic characteristics of the heavy vehicles which performed lane changing manoeuvre.

The trajectory dataset which is used in this study provides information on the heavy vehicles that perform the lane changing manoeuvres as well as the heavy vehicles with no lane changing manoeuvre and their surrounding traffic. The vehicles for which information would be available during the lane changing are presented in Figure 2.

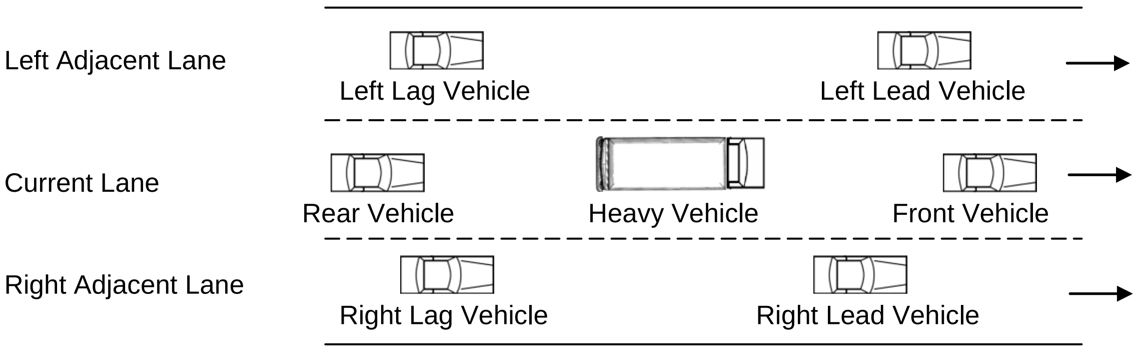



Figure 2: The heavy vehicle and the surrounding vehicles in lane changing manoeuvre.

The trajectory dataset makes it possible to determine the positions, speeds and accelerations of heavy vehicle and the surrounding vehicles (Figure 2) and the space gaps between the heavy vehicle and the surrounding vehicles at discrete time points. Due to the noise in the NGSIM dataset, the dataset was aggregated at each 0.5 second time interval. Then, the aggregated trajectory data at each 0.5 second time interval (2 observations per second) was used in this study.

## 4. THE LANE CHANGING DECISION MODEL

The lane changing decision comprises two stages: motivation to change lanes and selection of the target lane (Moridpour et al. 2008; 2009). In this study, the lane changing decision is defined as an integration of these two stages of lane changing decision. Therefore, the lane changing decision is defined as the motivation of selecting either the right adjacent lane (slower lane) or the left adjacent lane (faster lane). The motivations for selecting either the slower lane or the faster lane are different. Drivers generally move into the slower lane to prevent obstructing the fast moving vehicles which approach from the rear. However, moving into the faster lane is generally with the aim of gaining some speed advantages. Therefore, two separate models are developed in this study for the lane changing decision of heavy vehicle drivers. These two models include: Lane Changing to Slower Lane (LCSL) and Lane Changing to Faster Lane (LCFL).

### 4.1 The fuzzy sets and systems for the lane changing decision model

The explanatory variables in motivating the heavy vehicle drivers to move into the slower lane include: the front space gap, the rear space gap, the lag space gap in the right lane and the average speed of the surrounding vehicles in the current lane. The average speed in the current lane is assumed to be the average speeds of the heavy vehicle and the front and rear vehicles. The explanatory variables in motivating heavy vehicle drivers to move into the faster lane include: the front relative speed, the lag relative speed in the left lane and the average speeds of the surrounding vehicles in the current lane and the left lane. The average speed in the adjacent lanes is the average speed of the first two lead and the first two lag vehicles in that lane.

The number of fuzzy sets which could be used for any of the explanatory variables in the lane changing decision model is restricted to drivers' perception capabilities. Lane changing manoeuvre has a high level of interaction between the driver who performs a lane changing manoeuvre and the surrounding traffic. For simplicity, two and three sets are used for each explanatory variable and the obtained results from two and three sets are compared to each other. The fuzzy set terms for LCSL model are presented in Table 2.

Table 2: Fuzzy set terms for LCSL model.

| Front Space Gap | Rear Space Gap | Right Lag Space Gap | Average speed in Current Lane |
|---|---|---|---|
| ***Two Sets*** | | | |
| Small | Small | Small | Low |
| Large | Large | Large | High |
| ***Three Sets*** | | | |
| Small | Small | Small | Low |
| Medium | Medium | Medium | Intermediate |
| Large | Large | Large | High |

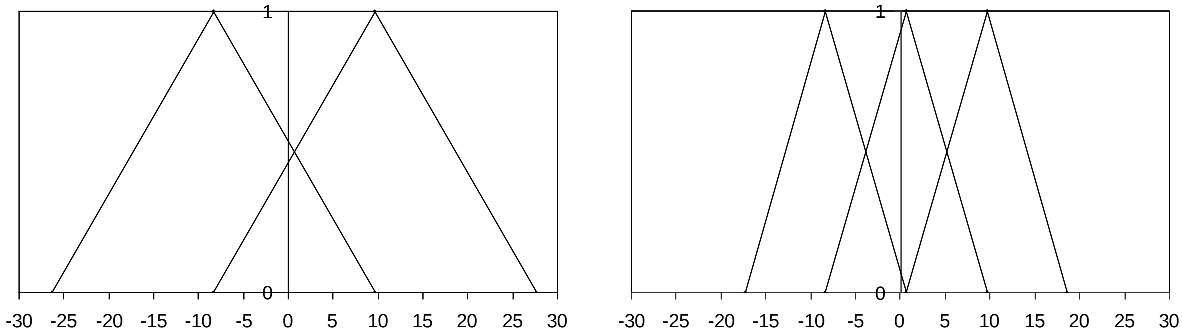
The size of the front space gap reveals the manoeuvrability level of heavy vehicles. The larger front space gap implies the lower manoeuvrability and the lower speed of heavy vehicles. Consequently, the vehicles which are at the rear may be obstructed by the slow moving heavy vehicle. Therefore, the heavy vehicle drivers move into a slower lane to make it possible that the rear vehicles have higher speed. Rear space gap may indicate the pressure on the heavy vehicles from the rear. The larger values of the right lag space gap provide the opportunity for heavy vehicle drivers to move into the right lane easily and safe. Finally, the average speed in the current lane indicates the speed difference between the heavy vehicles and the surrounding traffic in current lane. The fuzzy set terms for LCFL model are presented in Table 3.

Table 3: Fuzzy set terms for LCFL model.

| Front Relative Speed | Left Lag Relative Speed | Average speed in Current Lane | Average speed in Left Lane |
|---|---|---|---|
| ***Two Sets*** | | | |
| Low | Low | Low | Low |
| High | High | High | High |
| ***Three Sets*** | | | |
| Low | Low | Low | Low |
| Intermediate | Intermediate | Intermediate | Intermediate |
| High | High | High | High |

The small values of the front speed and consequently the desire to gain speed advantages may motivate the heavy vehicle drivers to move into the faster lane. The small values of the lag vehicle speed in the left lane provide the opportunity for heavy vehicle drivers to perform a safe lane changing manoeuvre. The average speeds in the current lane and the left lane specify the speed difference between the current lane and the left lane. Therefore, the speed advantage of drivers by moving into the left (faster) lane is indicated by these two variables.

The triangular membership function is used for all fuzzy sets in heavy vehicle drivers' lane changing decision model. The membership function for two and three fuzzy sets of the "Front Relative Speed" variable is presented in Figure 3.




(a) Two fuzzy sets. (b) Three fuzzy sets.

Figure 3: The membership function for the "Front Relative Speed" variable.

## 4.2 The fuzzy rule base of the lane changing decision model

The fuzzy rule base of the lane changing decision model, describes the heavy vehicle drivers' decision to move into either the right or the left lane, based on the above mentioned explanatory variables. Typical fuzzy rule for LCFL model with two and three sets, in natural language are presented below.

*If (Front Relative Speed is Low) and (Left Lag Relative Speed is Low) and (Average speed in Current Lane is Low) and (Average speed in Left Lane is High) then (LCFL is yes).*

*If (Front Relative Speed is Low) and (Left Lag Relative Speed is Intermediate) and (Average speed in Current Lane is Low) and (Average speed in Left Lane is High) then (LCFL is yes).*

# 5. MODEL VALIDATIONS

To examine the efficiency of the calibrated heavy vehicle drivers' lane changing decision model, the number of estimated lane changing manoeuvres of heavy vehicles are compared to the observed number of heavy vehicle lane changing manoeuvres in real world.

The number of observed heavy vehicle lane changing manoeuvres was insufficient to provide two different datasets for calibrating the model and validating its accuracy. Therefore, the leave-one-out cross-validation method was used to examine the accuracy of the developed model in estimating heavy vehicle drivers' lane changing decision. Leave-one-out cross-validation method uses a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data. The advantage of this method is that all observations are used for both training and validation and each observation is used for validation exactly once.

A total of 200 LCSL observations which is 13 lane changing manoeuvres and 204 non-lane changing observations (12 non-lane changing manoeuvres) were used to develop the LCSL model. In addition, 99 LCFL observations (8 lane changing manoeuvres) and 102 non-lane changing observations (6 non-lane changing manoeuvres) were used to develop the LCFL model. Then, the leave-one-out cross-validation method was used to examine the accuracy of the developed models in two sections. First, a single observation was selected as the validation data from all observations, and the remaining observations were selected as the training data. This was repeated for all observations and the correctly and the incorrectly estimated observations were counted. Second, all observations which belong to a single manoeuvre were selected as the validation data and the remaining manoeuvres were selected as the training data. This was repeated for all manoeuvres and the correctly and the incorrectly estimated manoeuvres were counted. The validation results for the LCSL and LCFL models are presented in Table 4.

Table 4: The validation results for LCSL and LCFL models.

| Model | Formulation Specifications | | Validation Results | | |
|---|---|---|---|---|---|
| | Explanatory Variables | No. of fuzzy sets | Matrix of Estimated Observations | Matrix of Estimated Manoeuvres | Correctly Estimated Observations |
| LCSL | Front Space Gap<br>Rear Space Gap<br>Lag Space Gap<br>Current Average Speed | 2 | 119 81<br>57 147 | 8 5<br>7 5 | 266 (65.8%) |
| | | 3 | 185 15<br>14 190 | 12 1<br>1 11 | 375 (92.8%) |
| LCFL | Front Relative Speed<br>Lag Relative Speed<br>Current Average Speed<br>Left Average Speed | 2 | 90 9<br>17 85 | 6 2<br>3 3 | 175 (87.1%) |
| | | 3 | 99 0<br>0 102 | 8 0<br>0 6 | 201 (100.0%) |

This table compares the validation results for the LCSL model and the LCFL model with two and three fuzzy sets. The matrix of estimated observations and the matrix of estimated manoeuvres show the results of the leave-one-out cross-validation method for the observations and manoeuvres respectively. In each matrix, the entry on the upper left corner presents the number of correctly estimated lane changes and the entry on the lower right corner represents the correctly estimated number of non-lane changes. The entries on the anti-diagonal represent the number of incorrect estimations. The entry on the upper right corner shows the number of incorrectly estimated lane changes and the entry on the lower left corner is the number of incorrectly estimated non-lane changes. Finally, the sum of two entries on the diagonal is presented as the correctly estimated observations.

In a comparative sense, the results in Table 4 show that the LCFL model has higher percentage and the LCSL model has lower percentage of accurately estimating the heavy vehicle drivers' lane changing decision. According to the trajectory data, a small proportion of the heavy vehicle drivers, move into the faster lane who mainly seek some speed advantages. The speed difference between the current and the left lane and therefore, the desire to move into the faster lane could be modelled by the microscopic traffic characteristics of surrounding vehicles in the current and left lanes. Meanwhile, the trajectory dataset shows that the heavy vehicle drivers mostly move into the slower lane. However, they may have other motivations for moving into the slower lane than only the microscopic traffic flow characteristics in the current and the right lanes. Therefore, it may be possible that the microscopic traffic characteristics of surrounding vehicles in the current and right lanes are insufficient to model the motivation of heavy vehicle drivers for moving into the slower lane. This may justify the higher percentage of accurately estimation in LCFL model and the lower percentage of accurately estimation in LCSL model.

The obtained results from Table 4 show that the models with three fuzzy sets are more accurate than the models with two fuzzy sets for each variable. As it was mentioned earlier, increasing the number of fuzzy sets increases the accuracy of the models. However, the number of fuzzy sets is constrained by the drivers' perception capability. Increasing the number of fuzzy sets enhances the model accuracy and meanwhile increases the required time for model development.

## 6. CONCLUSIONS

Lane changing manoeuvres of heavy vehicles have a significant effect on surrounding traffic characteristics due to the physical effects that the heavy vehicles impose on surrounding vehicles. These effects are the result of heavy vehicles' length, size, weight and limitations in their manoeuvrability. Therefore, it is important to have an exclusive lane changing behaviour model for heavy vehicle drivers.

This paper presented an exclusive fuzzy logic lane changing decision model for heavy vehicle drivers on freeways. The freeway trajectory data which was used in this study is under heavy traffic conditions. The lane changing decision was defined as the motivation of selecting either the right adjacent lane (slower lane) or the left adjacent lane (faster lane). Then, two separate models were developed for the lane changing decision of heavy vehicle drivers. These two models include: Lane Changing to Slower Lane (LCSL) and Lane Changing to Faster Lane (LCFL). Finally, the leave-one-out cross-validation method was used to examine the accuracy of the developed models in estimating the observations as well as manoeuvres. The obtained results showed that the LCFL model has higher percentage and the LCSL model has lower percentage of accurately estimating the heavy vehicle drivers' lane changing decision. This may be due to the fact that heavy vehicle drivers mainly move into the faster lane to gain speed advantages which could be modelled by the microscopic traffic characteristics of surrounding vehicles in the current and left lanes. However, the heavy vehicle drivers may have other motivations for moving into the slower lane than only the differences in microscopic traffic characteristics in the current and the right lanes.

Initial results obtained from comparison of the estimated lane changing manoeuvres and the observed ones are very encouraging. However, further research is required to compare the precision of the new developed model with the current lane changing models which have been applied in microscopic traffic simulation softwares.

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