Modelling Lane Changing Behaviour of Heavy Commercial Vehicles

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1 Introduction

Lane changing manoeuvre and specially lane changing manoeuvre of heavy vehicles has a high level of interaction among all vehicle movements. Lane changing manoeuvre has a significant effect on macroscopic and microscopic characteristics of traffic flow due to its interfering nature. Traffic congestion has a significant effect on driving patterns and the lane changing behaviours of drivers. It is believed that, drivers have different lane changing patterns in free flow conditions and congested traffic conditions.

Traffic volume in motorways increases rapidly and this considerable growth intensifies the importance of comprehending drivers behaviour (Wright 2006). Understanding the drivers' behaviour in lane changing manoeuvre is important due to its implication in variety of traffic and transport modelling such as:

- Transportation planning and traffic management strategies,
- Safety studies and capacity analysis,
- Speed oscillation and its effect on road capacity and safety,
- The effects of lane changing on traffic flow patterns,

This paper provides a review on existing lane changing models and their suitability to model lane changing behaviour of heavy vehicles. In addition, this paper explains the limitations of the current lane changing models in estimating the lane changing behaviour of heavy vehicles. Furthermore, it will present a framework to capture the lane changing behaviour of heavy vehicles. Finally, some insights to future work are presented.

2 Literature review

Many studies have been undertaken on the lane changing behaviour of drivers based on different approaches. These studies have been conducted to consider the lane changing behaviour, for different purposes. The different approaches in lane changing behaviour studies and their classifications are summarized in Figure 1. Lane changing behaviour studies are undertaken for some important purposes.

2.1 Driving Assistance Models

The first significant purpose of lane changing behaviour studies is its application in capacity analysis and road safety studies (Hetrick 1997; Zwaneveld and Arem 1997; Godbole et al. 1998; Lygeros et al. 1998; Nagel et al. 1998; Hoogendoorn and Bovy 2001; Knospe et al. 2002; Hatipoglu et al. 2003; Dijck and Heijden van der 2005). To improve the capacity and safety aspects of the road, driving assistance models has received attention in recent years. Therefore, several lane changing models for collision prevention and automation purposes have been developed to improve the road capacity and road safety which are out of the scope of this study.

2.2 Driving Performance Models

The second significant purpose of lane changing behaviour studies is to find out the drivers' lane changing patterns in different traffic conditions and different situational and environmental characteristics. Find out drivers' lane changing patterns in different traffic conditions is useful to develop driving performance models. Lane changing performance models are applied to simulate the drivers' lane changing behaviour through microscopic traffic simulators. Lane changing performance models can be categorized into tactical lane changing models and operational lane changing models as it is shown in Figure 1. Drivers' behaviour can be categorized into three broad categories based on drivers' response to their environment. These three categories are: strategic, tactical and operational (Sukthankar et al. 1997). At the highest level, which is the strategic level, the route is chosen and the goals of the trip are determined. At the intermediate level which is the tactical level, manoeuvres are selected to achieve the short term objectives such as decision to pass a slow moving vehicle. At the lowest level which is the operational level, the manoeuvres are converted to control operations. Therefore, in the following sections, the previous studies on tactical and operational lane changing behaviour will be explained with more details.

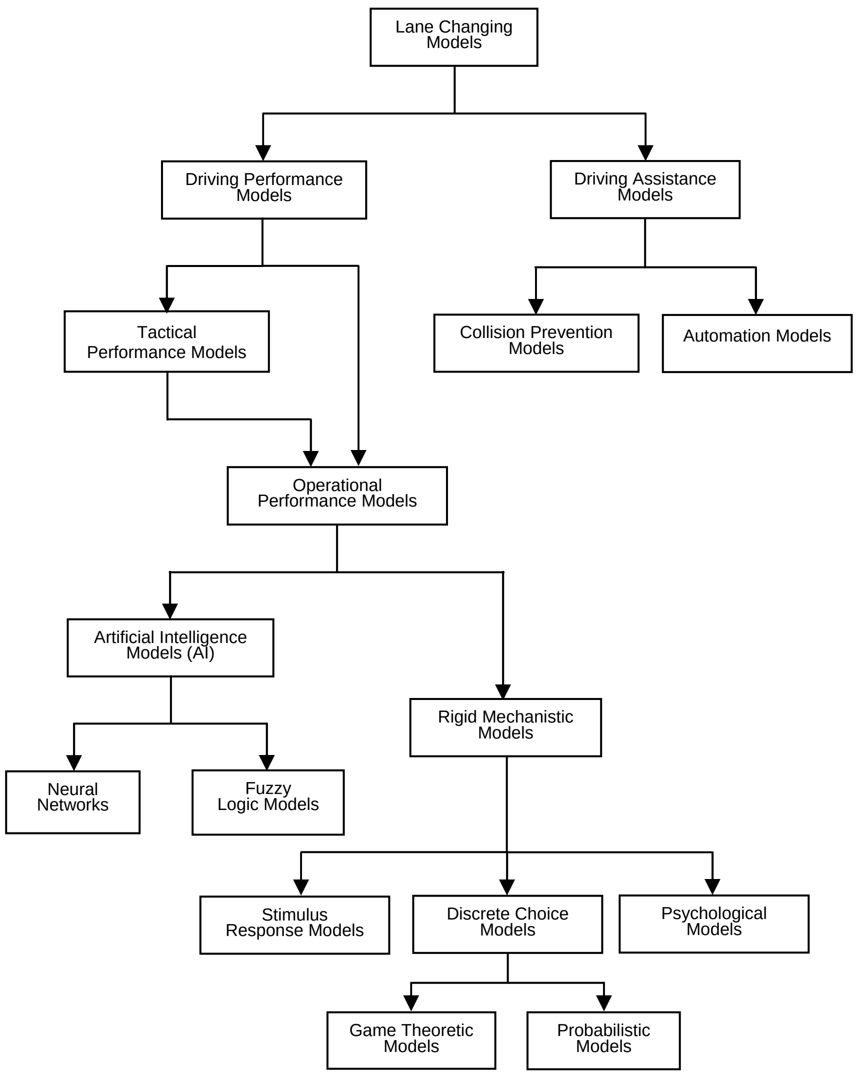

Figure 1: Classification of available approaches in lane changing behaviour studies

2.2.1 Tactical performance models

Webster et al. (2007) developed and evaluated a tactical lane changing model, using a forward search algorithm to represent driver's anticipation and manoeuvre planning behaviour. The forward search algorithm generates a branching tree of sequential actions for each modelled vehicle at each time interval in the simulation. This algorithm, takes into account the changes in the state of the subject vehicle and surrounding vehicles to generate a branching tree of sequential actions. Each branch represents a particular action which is chosen by the driver and also the events which would be probably occurred as a reason of this set of choices. The sequence of actions leading to the best outcome is then selected and the subject vehicle applies the first action of that sequence.

Although the model Webster et al. developed, has better performance than the basic lane changing models, they used several simplifying assumptions. First, in the forward search tree, the surrounding vehicles do not change their car following situation and they can not perform lane changing manoeuvre. This assumption is in contrast to real traffic behaviour in which the behaviour of the subject vehicle affects the behaviour of the surrounding vehicles and the surrounding vehicles decide on their driving behaviours considering the behaviour of the subject vehicle. Second, in the forward search tree, the subject vehicle's lane changing decisions were restricted to situations that an acceptable gap in the adjacent lane was available. This assumption is only acceptable in free flow conditions and in congested traffic conditions the acceptable gaps are prepared by either the lag vehicle's courtesy or the subject vehicle's forcing. Finally, the developed model is only for Discretionary Lane Changes (DLC) which normally takes place with the aim of speed advantages. Discretionary lane changes perform when the driver is not satisfied with the driving situation in the current lane and wants to gain some speed advantages.

Schlenoff et al. (2006) developed a hierarchical multi resolution framework for moving object prediction which incorporates multi prediction algorithms into a single framework. They tried to develop a framework in which the results from a short term prediction algorithm can be used for strengthen or weaken a situation based long term prediction algorithm's results. In long term prediction algorithm, for each vehicle on the road the current position and speed of the vehicle is given to the algorithm and for each possible future action, the algorithm creates a set of next possible positions and assigns a cost to each action. The cost is based on the traffic characteristics of the surrounding vehicles and the distance of the vehicle from the obstacle. The total cost is the sum of the encountered costs by performing each action. Based on the cost of each action, the algorithm computes the probability for that action. The algorithm also builds the predicted vehicle trajectories for each vehicle, based on the possible path each vehicle will have in a predetermined time interval. Then algorithm recalculates the vehicle's position set and their probabilities and finally, the future position of each vehicle is determined based on the highest probability of the possible locations.

To combine the results of two algorithms, Schlenoff et al. developed a new methodology. For each vehicle, set of positions and probabilities is gained and the distance between the positions obtained from the short term and long term algorithms is computed. If the distance was less than a threshold, there was no need for adjustment and the most probable position from the long term algorithm was the answer, else the distance between results of the short term algorithm and the other positions obtained from the long term algorithm were calculated and the position with the least distance which was less than the threshold was accepted as the next position and all other probabilities should be adjusted and scaled accordingly.

2.2.2 Operational performance models

Operational performance behaviours are the lowest level of drivers' behaviour to control operations. To perform an operational behaviour, the driver considers only the near future.

Consequently, in an operational lane changing manoeuvre, the driver only considers the traffic situation in the near future to perform lane changing. These models are useful in simulating the lane changing patterns of drivers. Different operational performance models are exploded in details, below.

2.2.2.1 Rigid mechanistic models

The rigid mechanistic models are those which make a relationship between explanatory variables and dependant variable. In these models the magnitude of the result depends on the amounts of the independent variables. Mechanistic lane changing approaches do not usually incorporate the uncertainties of drivers' perception and decision.

- *Stimulus response models*

Wiedemann and Reiter (Wiedemann and Reiter 1978), developed a theoretical lane changing model to explain the human decision process during the lane changing. This lane changing model is influenced by the driver's perception of the surrounding vehicles. They assumed that human driving behaviour is naturally distributed and different drivers have different characteristics. These different driving characteristics can be observed in driving capabilities, abilities in perception and estimation, needs of safety, desired speed and maximum acceptance of acceleration and deceleration which characterises drivers' aggressiveness.

Wiedemann and Reiter assumed that the drivers' lane choice is influenced by their own wishes about driving and based on this assumption they distinguished between the lane changes from the slower to the faster lanes and from the faster to the slower lanes. In their model, the desire to perform a lane change to the faster lane can be a result of an obstruction caused by a slow moving vehicle in the current lane and the level of obstruction can be a function of the differences between the speed of the front vehicle and the desired speed of the subject vehicle. In their model, the decision to change into the slower lane can be the reason of an obligation to be in the right lane or to allow a faster vehicle to pass. A change to a slower lane is accepted only when the subject vehicle will not be obstructed by a slow moving vehicle for a specific time interval. Finally, changes to both faster and slower lanes are possible if the manoeuvre is safe. This safety can be evaluated by the distance and speed differences of the subject vehicle and the front and rear vehicles in the current lane and the lead and lag vehicles in the target lane. Assuming that all drivers' decisions are based on human perceptions, they classified the surrounding influences as actual influences and potential influences. Actual influences are the real surrounding vehicles' characteristics which influence the driver's perceptions and decisions such as distances and relative speeds. Potential influences are the driver's estimation of the surrounding vehicles' situations in the near future.

Gipps (1986), proposed a framework for the structure of lane changing decisions and the execution of lane changing. This framework can be used to explain the lane changing behaviour in freeways and urban streets where traffic signals, obstructions and heavy vehicles influence the decision procedure. In Gipps's model, the driver's decision to change lane is the result of considering three factors including: whether it is physically possible and safe to change lanes, whether it is necessary to change lanes and whether it is desirable to change lanes.

Gipps defined three zones to characterize the drivers' behaviour during the lane changing manoeuvre. These three zones are based on driver's distance to his intended turn. When the turn is in far distance, it has no effect on driver's lane changing decision and the driver tries to maintain the desired speed. When the turn is in middle distance, the driver ignores the opportunities which have speed advantage but require having a lane change in a wrong direction. When the driver comes close to turning movement, he should be in the correct lane or the adjacent lane and gaining speed advantage is not important.

Gipps lane changing model has been developed on the basis of his car following model which makes some limits on the driver's braking rate to have a safe speed respect to the preceding vehicle and also this safe speed is limited by the driver's desired speed in order to prevent the influence of the vehicles or obstructions far from the vehicle on the driver's decision. His lane changing model is a simple model and the revised version of this model is applied in several microscopic traffic simulators. Despite, the popularity of Gipps lane changing framework, his model has some assumption problems. He assumes that the lane changing occurs when a gap of sufficient length is available and it is safe to change lane which causes some limitations in congested traffic conditions. Moreover in Gipps's model, the zones are defined deterministically and he did not consider the differences between drivers and even within drivers over time.

Although the lane changing models which are based on stimulus responses are simple models and the whole decision process is considered in one model, but it is difficult to calibrate the model parameters. Also, the applied explanatory variables are some primary variables and a simple framework has been applied to model the lane change decision. The general procedure of developing a stimulus response model, the considered stages in a lane changing model which is based on stimulus responses, the considered explanatory variables and the strengths and the weaknesses of this model type are summarized in Table 1.

- *Discrete choice models*

Discrete choice models can be applied in developing probabilistic lane changing models. Ahmed (Ahmed 1999) developed a probabilistic model to describe the lane changing behaviour, based on discrete choice framework. He modelled the lane changing behaviour as a sequence of three stages: decision to consider a lane change, choice of the target lane and acceptance of a gap of sufficient size in the desired lane to execute the lane changing decision.

Ahmed categorized the lane changing movements into three classes, Mandatory Lane Changes (MLC) and Discretionary Lane Changes (DLC) and forced merging. Mandatory lane changes happen when a driver is forced to leave the current lane because of taking an exit off ramp, an obstruction or lane blockage in the current lane or lane use regulation. Discretionary lane changes perform when the driver is not satisfied with the driving situation in the current lane and wants to gain some speed advantages. For instance when the average speed of a lane is less than the desired speed of the driver or when the driver is obstructed by a slow moving heavy vehicle. Forced merging takes place in heavily congested traffic conditions, when the gap of the sufficient size is created through courtesy or forcing. In his model, in the first stage, if the driver is not satisfied with driving conditions in the current lane, neighbouring lanes are compared to the current lane and the driver selects a target lane. Lane utilities are determined by defined explanatory variables in the target lane choice model. In the second stage, a gap acceptance model is used for lane changing performance. The mathematical formulation of the discrete choice framework for the lane changing procedure in his model included three different utility functions for decision to consider a lane change, choice of the target lane and choice of the acceptable gap. These utility functions are applied to find out the probability of having a lane change manoeuvre.

The lane changing models developed by Ahmed, did not capture the trade off between mandatory and discretionary lane changing decision process. Also, his model, as Gipps's model, assumed that the existence of the MLC situation is determined based on the distance to the exit off ramp. Moreover, he considered the lane changing behaviour of heavy vehicles only in the DLC models as a dummy variable. Definition of a dummy variable to consider the effect of heavy vehicles as the subject vehicle just captures the difference in the size of the acceptable gaps between passenger cars and heavy vehicles and did not consider the vast differences in the operational characteristics of the passenger cars heavy vehicles. The effect of heavy vehicles as the subject vehicle only considered in DLC models because the number of observations was not adequate in the MLC and forced merging and the defined dummy variable as the subject vehicle was not meaningful.

Toledo (Toledo 2003), developed an integrated probabilistic lane changing model which allows drivers to consider both mandatory and discretionary lane changes at the same time. He used a discrete choice framework to model the lane changing decision process. In his model, the decision process for the lane changing manoeuvre was considered as two steps: choice of the target lane and the gap acceptance decision. He classified the efficient explanatory variables in lane changing behaviour into four categories: neighbourhood variables, path plan variables, network knowledge and experience, and driving style and capabilities. He defined a target gap choice set for the gap acceptance of the subject vehicle. In his target gap choice set, the subject vehicle can select the gap next to the subject vehicle in the target lane, or the forward gap or the backward gap in the target lane. Also he developed an acceleration/deceleration model to capture the acceleration/deceleration behaviour of the subject vehicle in choosing the target gap. A typical formulation of the lane changing behaviour which is based on Toledo's work is shown in Equations 1, 2 and 3. Equation 1 is to model the target lane choice and the Equation 2 is for modelling the gap acceptance behaviour.

$$U_n^{lanei}(t) = X_n^{lanei}(t)\beta^{lanei} + \alpha^{lanei} v_n + \varepsilon_n^{lanei}(t) \qquad lanei = CL, RL, LL \qquad (1)$$

Where,

$U_n^{lanei}(t)$ = the utility of lane *i* to driver *n* at time *t*,

$X_n^{lanei}(t)$ = the random term associated with the lane driver/vehicle,

β^{lanei} = the corresponding vector of parameters,

$\varepsilon_n^{lanei}(t)$ = the random term associated with the lane utility,

v_n = the driver specific random term.

To model the gap acceptance behaviour, he defined a critical gap and assumed that if the size of the observed gap is larger than the critical gap, the gap will be accepted and if the size of the gap is less than the critical gap, the gap will be rejected. The formulation of the critical gap is shown in Equation 2.

$$\ln(G_n^{gapg \quad TL,cr}(t)) = X_n^{gapg \quad TL}(t)\beta^{gapg} + \alpha^{gapg} v_n + \varepsilon_n^{gapg}(t) \qquad gapg = lead, lag \qquad (2)$$

Where,

$G_n^{gapg \quad TL,cr}(t)$ = the critical gap *g* in the target lane measured in meters,

$X_n^{gapg \quad TL}(t)$ = the vector of explanatory variables affecting the critical gap *g*,

β^{gapg} =the corresponding vector of parameters,

$\varepsilon_n^{gapg}(t) \sim N(0, \sigma_{gapg}^2)$ =the random term,

α^{gapg} =the parameter of the driver specific random term v_n.

Also, it should be mentioned that to accept a gap, both the lead and the lag gaps should be larger than the critical lead and critical lag gaps which is considered in Equation 3.

$$P_n(\textit{Change to target lane} \mid TL_t, v_n) = \qquad (3)$$

$$P_n(\textit{Accept lead gap} \mid TL_t, v_n) P_n(\textit{Accept lag gap} \mid TL_t, v_n) =$$

$$P_n(G_n^{leadTL}(t) > G_n^{leadTL,cr}(t) \mid TL_t, v_n) \cdot P_n(G_n^{lagTL}(t) > G_n^{lagTL,cr}(t) \mid TL_t, v_n)$$

Where,
$TL \in \{RL, LL\}$ = the target lane which is left lane or right lane,
$G_n^{leadTL}(t), G_n^{lagTL}(t)$ = the available lead and lag gaps in the target lane.

Choudhury et al. (Choudhury et al. 2007) developed a merging behaviour framework which integrated normal, cooperative and forced merging components of a lane changing behaviour at the same time. In congested traffic conditions, usually, acceptable gaps are not available and the merging manoeuvre is a more complicated behaviour. For instance, drivers may merge into the target lane through the courtesy of the lag driver in the target lane or they may force in and compel the lag vehicle in the target lane to slow down and prepare the gap of sufficient size. The probabilistic model that they developed to model the lane changing process during the congested traffic conditions consists of three steps. In the first step, in the normal merging process each driver compares the available lead and lag gaps in the through lane with the critical lead and lag gaps which are the minimum acceptable and safe gaps to merge in and if the available gaps are greater than the critical gaps, the driver merge into the through lane. In the second step, if the gaps are not acceptable, the merging vehicle evaluates the speed, acceleration and position of the through vehicles and anticipates whether the lag vehicle in the through lane, prepares courtesy for the driver. If the lag vehicle in the through lane decides to prepare courtesy to the merging vehicle, starts to decelerate and therefore the gap starts to increase. The size of the anticipated gap depends on the length of the time which is considered to estimate the length of the gap and also the driver's perception and planning abilities to estimate the length of the gap. In the third step, if the anticipated gap is not acceptable, the driver considers whether to remain in the merging lane or compels the lag driver in the target lane to slow down and prepare the adequate gap for him to merge in. This decision depends on the urgency of the merge and driver's level of aggressiveness and also traffic condition.

The general procedure to develop a probabilistic model, the considered stages in a probabilistic lane changing model, the explanatory variables which normally used to develop this type of lane changing model and the strengths and the weaknesses of this model type are summarized in Table 1.

Discrete choice models can be applied in developing game theoretic models. Game theory is a mathematical model to study the decision making activities of the people, based on their level of information (Kita 1999). Pei and Xu (Pei and Xu 2006) developed a lane changing structure which constitutes two types of lane changing behaviour in congested traffic conditions, based on game theory. They established a model for lane changing manoeuvre, based on traffic information and the drivers' experiences and developed a model for drivers' cooperation based on time and load security.

Pei and Xu modelled the forced lane changing in congested traffic conditions through a game among the subject vehicle and the target lag vehicles. The driver who wants to merge into the target lane may choose the waiting tactic to improve the safety and prevent crashes, but as the time elapses, the necessity of lane changing will be more important and the subject vehicle performs a forced lane changing while the follower in the target lane reduces the speed to prevent any crash. They mentioned that the vehicle in the target lane will increase his benefits by reducing the speed and preparing a sufficient sized gap for the subject vehicle to perform a lane changing manoeuvre and also will increase the subject vehicle's benefits. They developed their game theoretic lane change model based on two assumptions. First, the subject vehicles' lane changing tactics was relevant to their waiting time and safety. In this model, they defined safety as the distance of the subject vehicle to the convergence point. While the waiting time was longer or the distance was shorter, the probability to change lane was stronger. Meanwhile, the lag vehicle's cooperation tactics was based on the safety and optimum travel time.

The general procedure to develop a game theoretic model, the stages of developing a game theoretic model, the explanatory variables and the strengths and the weaknesses of this model type are presented in Table 1.

- *Psychological models*

The French National Institute for Research in Transportation and Safety, INRETS, developed a driving behaviour model which can run either as an ordinary traffic simulation model or host a driving simulator which called is ARCHISIM (Espié et al. 1994; Champion et al. 2001; El Hadouaj et al. 2000). This psychological model has been developed based on the concept of decision making during driving. In ARCHISIM, the behaviour of the subject vehicle is based on a few fundamental principles. Each driver tries to minimize the interaction with his environment, including other drivers and road characteristics. Within ARCHISIM, drivers are simulated in virtual vehicles and each driver has a model of his environment and interacts with the other vehicles (passenger cars, trucks, trams, etc), the infrastructure (traffic lights controllers) and the road. Within ARCHISIM, each driver has specific skills, aims and characteristics and also drivers are autonomous and can potentially react to any situations.

Driving aggressiveness has influence on some characteristics of the traffic such as traffic flow and also influence on the probability of vehicle accidents (Moussa 2004). According to Moussa, traffic density and driving aggressiveness are the most important parameters, influencing the traffic characteristics. Therefore, understanding the driving aggressiveness is an important issue in driving behaviour studies such as lane changing.

Tasca (2000) reviewed the literature on aggressive driving behaviour and the causes of them. He mentioned that there are three main categories of characteristics which contribute the aggressive driving: Situational and/or environmental conditions, Personality or dispositional factors and Demographic variables. Reviewing the literature, Tasca categorized the following factors as the main determinant characteristics in aggressive driving behaviours:

- Age (e.g. younger drivers are more likely to show aggressiveness),
- The traffic situation which cause anonymity (e.g. darkness),
- Obstructing by unexpected traffic congestion,
- The driver’s believe in his or her driving skills,
- Generally being aggressive in all social activities.

According to his studies, some of the specific behaviours which constitute aggressive driving can be classified as follows:

- Tailgating,
- Driving at high speeds which is more than the norm and results in frequent tailgating and frequent and abrupt lane changing,
- Weaving in and out of traffic,
- Improper passing (e.g. cutting in too close in front of vehicles being overtaken),
- Improper lane changing,
- Failure in giving the right of way to another drivers or road users,
- Unwillingness to cooperate to other drivers unable to merge or change lanes due ton traffic conditions,
- Passing on the road shoulder or passing on the right,
- Preventing other drivers from passing.

Laagland (2005) selected three microscopic traffic simulators to model the level of aggression of drivers in his studies. These three microscopic traffic simulators were: AIMSUN, MITSIM) and PARAMICS. According to his studies, one of the most important issues in modelling the drivers’ level of aggressiveness is to find out the intensity of the stimulus. This means to comprehend the level of influence each main determinant characteristic have in aggressive driving behaviours of the driver (weight of a certain stimulus). For instance, what level of congestion will cause a driver to drive more aggressively and how long does this factor influence the driver's aggressiveness. He assumed that the mood of a driver while he is driving can represent driving level of aggressiveness. The variable factors which influence the level of aggression cause a temporarily emotional reaction. This affects the driver's mood for a period of time. Laagland used a simplified algorithm of Velasques, which is an emotional algorithm, to model the level of aggression of drivers. He defined the level of emotion at each time interval and determined the intensity of that emotion.

2.2.2.2 Artificial intelligence models (AI)

Rigid mechanistic models do not incorporate the inconsistencies and uncertainties of driver perception and decisions (McDonald et al. 1997). These models quantify variables into crisp magnitudes (Das et al. 1999). In recent years, several approaches have become popular to solve the problems of rigid mechanistic models. Some of these approaches are the approaches which are based on Artificial Intelligence (AI). AI approach primarily focuses on the development of systems which can learn rules automatically from repeated exposure to data, so called neural networks. Although these models are useful, but if any additional input adds to this type of models, they should be reconstructed again.

One of the other types of AI, which is Fuzzy logic, allows defining a quantifiable degree of uncertainty in the model and in this way reflects the natural or subjective perception of real variables. In Fuzzy logic models, the parameter space which can be observed in real world, are divided into a number of overlapping sets and each one is associated with a particular concept (McDonald et al. 1997).

Das et al. (1999) proposed a new microscopic simulation methodology based of Fuzzy IF_THEN rules and they called their software package as AASIM (Autonomous Agent Simulation Package). The major motivation of using a fuzzy knowledge based approach to model the driver behaviour is because fuzzy modelling provides an effective means to change any highly nonlinear system into IF-THEN rules. In addition, fuzzy logic is well equipped to handle uncertainties that are present in real world traffic situations. In their microscopic simulation methodology, lane changes are classified as mandatory and discretionary lane changes and the mandatory lane change occurs either due to approaching exits or when the vehicles current lane merges into another one.

In AASIM, to decide when a mandatory lane change happens, the mandatory lane change fuzzy rules consider not only the distance to the approaching exit or merge point, but also the number of lane changes that are required. When multiple lane changes are required, the probability of making a decision to change lane increases. In their framework, the decision output is a binary (yes or no) answer. The discretionary lane change rules of AASIM provide a binary decision which is based upon two parameters, the driver's speed satisfaction level and the congestion levels of the lanes in the adjacent left or right lanes. The driver speed satisfaction is based on the history of the speed that the driver has been driving.

In AASIM, after the driver decides to perform a lane changing manoeuvre, the gap finding is the next stage. The fuzzy rules try to find all the required data for car following and also speeds and gaps of the vehicle in the destination lane, and calculate an acceleration value which is different from that generated by the normal car following rules. If there is an acceptable size of gap in the destination lane, the gap finding rules enable the vehicle to speed up or slow down to make itself closer to the gap, but at the same time consider the safe space with the lead vehicle in the present lane. The variables which are considered in AASIM's gap finding model include; speed, forward gap, forward speed, forward gap in the destination lane, back gap in the destination lane, forward speed in the destination lane, back speed in the destination lane. The last stage in AASIM lane change model is setting the gap acceptance rules. These rules look for the gaps and speeds of the vehicle ahead and behind the vehicle in the destination lane, the distance to the next exit or lane merger (infinite for discretionary lane changes). The variables which are considered in AASIM's gap acceptance rule are forward gap in the destination lane, back gap in the destination lane, forward speed in the destination lane, back speed in the destination lane, and exit/merger distance.

A typical formulation of the lane changing behaviour which is based on Das et al.'s work is shown in Equations 4 and 5. The discretionary lane change model is based on traffic congestion in the target lane and the driver's satisfaction level. Equation 4 models the driver's satisfaction level and the traffic congestion in the target lane is modelled through Equation 5.

$$\sigma^{(new)} = (1-\varepsilon)\times\sigma^{(old)} + \varepsilon\times\left(\frac{v}{v_{\min}}\right) \quad (4)$$

Where,
σ = driver's satisfaction, which is the history of how fast the driver has been driving,
v = the speed of the vehicle during the current iteration,
$v_{\lim}$ = the speed limit of the freeway,
ε = constant quantity called the satisfaction learning rate.

$$c = \frac{\sum_i e^{-\frac{d_i}{\Delta}} \times \left(1-\frac{v_i}{v_{\lim}}\right)}{\sum_i e^{-\frac{d_i}{\Delta}}} \quad (5)$$

Where,
c = the local lane congestion,
d_i = the distance of the i^{th} vehicle,
Δ = a constant.

McDonald et al. (1997) and Wu et al. (2000) described the development of a fuzzy logic motorway Simulation model (FLOWSIM) and also tried to establish fuzzy sets and systems for motorway driving behaviour models. To model the lane changing behaviour, they classified the lane changing manoeuvres into two different categories including; lane changing to the near side which is mainly to prevent disturbing the fast moving vehicles which approach from behind and the lane changing to the off side lane with the aim of getting speed advantage. To establish the offside lane changing model they defined two variables; overtaking benefit and opportunity. The overtaking benefit is defined by the speed gain when an offside lane change is performed, and the opportunity is about the safety and comfort of the lane changing manoeuvre, which is measured by the time headway to the nearest approaching rear vehicle in the offside lane. The near side lane changing model uses two variables, pressure from rear and gap satisfaction in the nearside lane. The variable pressure from rear is the time headway of the following vehicle, while gap satisfaction is defined as the period of time for which it would be possible for the subject vehicle to stay in the gap in the nearside lane, without reducing speed.

The general procedure and the stages to develop a lane changing fuzzy model, the explanatory variables and the strengths and the weaknesses of fuzzy models are summarized in Table 1.

2.3 Limitations of existing lane changing models

Reviewing the literature, major limitations of previous studies are revealed in the existing lane changing behavioural models. They are summarized below:

- ***A specific lane changing behaviour model for heavy vehicles,***
  There have been many passenger car lane changing models described in the literature. However, none of the previous studies dealt with the lane changing behaviour of heavy vehicles.

Table 1: The efficient operational performance models[1] in lane change modelling and their characteristics

Model Types			
Stimulus Response	Probabilistic	Game Theoretic	Fuzzy Logic
General Procedure to Develop the Model			
• Decide on dependant variables, • Calibrate the models.	• Decide on: 1- Independent options, 2- Dependant variables, • Calibrate the probabilistic functions.	• Decide on: 1- Number of players, 2- Players' benefit function, 3- Type of the game, 4- All relevant human responses, • Calculate the pay off matrices.	• Decide on: 1- Dependant variables, 2- Linguistic terms (sets) and membership function, 3- Rule sets for inference system, • Calibrate the fuzzy models.
Considered Stages in Lane Changing Model Developments and Explanatory Variables (EV)			
1. Decide on a MLC or DLC. EV: Maximum subject's safe speed and brake, front vehicle's location and the effective length, subject's estimation of front's brake. 2. Decide on a lane change to the faster lane or the slower lane. EV: Duration and length of the lane change manoeuvre, time and distance headway to surrounding vehicles.	• Decide to have a lane change, EV: MLC-Exit/merger distance, number of lane changes, DLC-Speed difference, deceleration of lead vehicle, presence of heavy vehicle, • Choose the target lane, EV: Subject speed, relative distance and speed to surrounding vehicles, presence of heavy vehicle, tailgating, avoid the right most lane, exit distance, • Accept a gap of sufficient size in the desired lane. EV: Subject's relative speed respect to lead and lag vehicle, relative lead and lag gaps.	• Choose players as the most interacting vehicles, • Choose the game type, • Define players' benefit function, • Define all available games of players, • Calculate the pay off matrices. EV: The subject's speed, the maximum safe speed for lane change, waiting time, maximum tolerated waiting time, traffic density in target lane and jam density.	1. Decide on MLC or DLC, • MLC or DLC, EV: MLC-Exit/merge distance, number of lane changes, DLC-Left and right lane congestion, driver satisfaction. • Find a gap in target lane, EV: Speed, front gap, and speed, lead and lag gap, lead and lag speed. • Acceptance of a gap. EV: Lead and lag gap, lead and lag speed, exit/merger distance. 2. Decide to have a lane change to left or right. EV: Left change-Motivation, opportunity, Right change-pressure, Gap satisfaction.
Strengths			
• Simplicity in modelling the lane changing manoeuvre, • Considering the whole decision process in one model, • Small number of applied variables.	• Decision on the basis of maximum gained utility, • At each stage, getting probabilistic results instead of binary answers (yes or no).	• Mathematical modelling of the drivers' decision making, • Considering the microscopic interactions between the interfering vehicles,	• Considering human's imprecise perception and decision base, • Incorporating more variables than the mathematical models, • Calibrating the model with an optimization algorithms, • Finding the fuzzy rules from numerical data.
Weaknesses			
• Difficulties in calibrating the model parameters, • Using primary variables and simple framework to model the lane change decision.	• Obligation to calculate all the probability functions to find the utility of each choice.	• Complexity in modelling the interactions between multiple players, • Difficulties in calculating the pay off matrices, • Simplicity in modelling the lane change as two- player game.	• Validation process of the membership functions, • Difficulties and complexity in abstracting fuzzy rules, • Needing specific data collection to define the fuzzy set thresholds.

[1] Psychological models and neural networks are not applicable to model the lane changing behaviour

- ***Drivers' level of aggressiveness,***
  Drivers' aggression has an undeniable influence on driving and lane changing behaviour of drivers. Despite the importance of drivers' aggressiveness and its effect on driving behaviour, in most of the current lane changing models, the drivers' level of aggressiveness have not been considered.
- ***Tactical lane changing behaviour,***
  To perform a lane changing manoeuvre, the driver considers the current state of the surrounding vehicles and the near future behaviour of surrounding vehicles at the same time. However, in most of the current lane changing models only the operational lane changing behaviour is considered and the tactical lane changing decision of drivers has been neglected. The available tactical lane changing models developed for passenger cars are very simple in their structure and many simplifying assumption has been applied to develop them. Therefore, these tactical lane changing models are not suitable for modelling lane changing behaviour of heavy vehicles.

3 A framework for lane changing behaviour of heavy vehicles

This section highlights the main contribution of this study, explains the aims of the study and proposes the work that will be carried out to achieve these aims. Contribution of this study is based on the limitations of the previous studies which are highlighted in the previous section. This study will develop a specific lane changing model for heavy vehicles during congested traffic conditions. Figure 2 shows the conceptual framework of this research.

3.1 Investigation of Lane Changing Characteristics

Heavy vehicles impose some physical and psychological effects on surrounding traffic. These effects are the result of two main factors: the physical characteristics of heavy vehicles (e.g. length and size) and their operational characteristics (e.g. acceleration, deceleration and manoeuvrability) (Al-Kaisy and Jung 2005). For better understanding of the differences between the behaviour of heavy vehicle drivers and passenger car drivers during the lane changing manoeuvre, their behaviour can be compared from a few seconds before the lane changing performance to a few seconds after the completion of lane changing. This comparison makes it possible to realize the difference between the explanatory variables in lane changing decision of heavy vehicles and passenger cars. Furthermore, for similar variables, it will be possible to compare the magnitudes of each variable and the thresholds of each variable for heavy vehicles and passenger cars (Figure 3).

3.2 Development of an operational and tactical lane changing model

There have been several studies in modelling the lane changing behaviour in the literature. However, in all of these studies the lane changing models have been developed for passenger cars. Some of the recent lane changing models indirectly tried to consider the lane changing behaviour of heavy vehicles through definition of a dummy variable (Ahmed 1999). In these models a dummy variable is defined which captures the vehicle type. If the lane changing vehicle is a heavy vehicle, the dummy variable's magnitude will be one and otherwise it is zero. They defined different sizes as the acceptable gaps for passenger cars and heavy vehicles. Moreover, they defined different speed limits for passenger cars and heavy vehicles. Therefore, their lane changing models only captures the difference between the size of the acceptable gap for the passenger cars and heavy vehicles and the differences in maximum speed. In real traffic, there is an interaction between the heavy vehicle which

decides to have a lane changing manoeuvre and the surrounding traffic. The adjacent vehicles have different driving patterns (e.g. speed, acceleration and headway) when the heavy vehicle wants to perform a lane changing manoeuvre.
Moreover, most of current lane changing models are based on short term goals or short term plans. This means that, in current lane changing models, only the operational behaviour of vehicles is considered and no significant attention has been paid to tactical lane changing behaviours and near term plans. Although there are some tactical lane change models in the literature, they are very simple in their structure and many simplifying assumption has been applied to develop them. The tactical lane changing behaviour is more important for heavy vehicle drivers, as most of them are professional drivers and are pretty familiar with the characteristics of the road. Moreover, because of the heavy vehicle's height, the drivers have a good view to see the surrounding traffic better than the passenger car drivers.

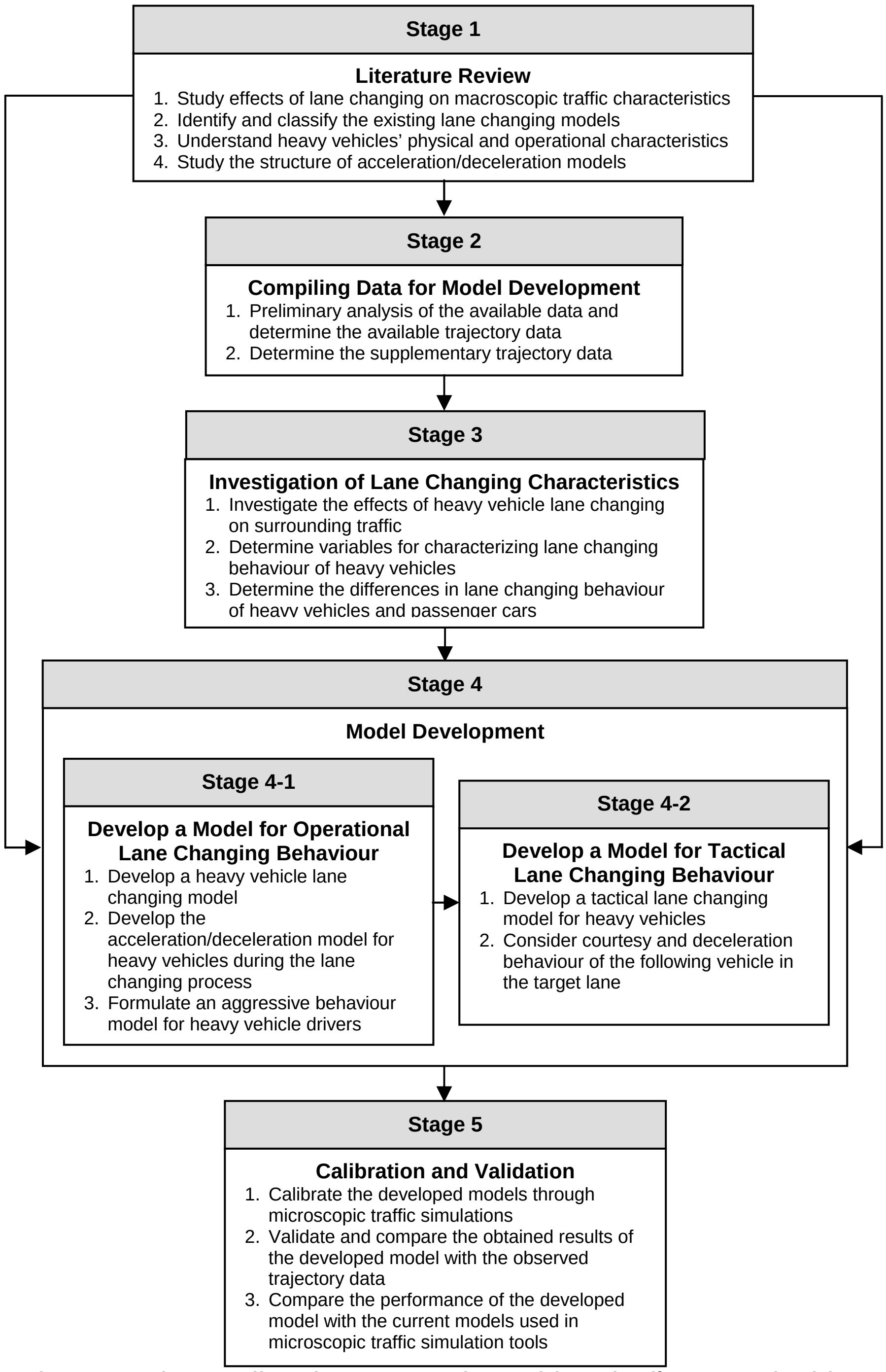

Figure 2: The predicted stages and considered milestones in this study.

Drivers' aggressiveness is another important issue in driving behaviour. The drivers' level of aggressiveness affects their driving patterns and behaviours and therefore, their lane changing behaviour. Based on the level of aggressiveness, the drivers have different sizes of acceptable gap, different levels of acceleration and deceleration and different speeds and headways. Also, different lane changing patterns are selected by drivers respect to their level of aggressiveness. These are some psychological models in the literature, which estimates the drivers' level of aggressiveness. However, in most of the current lane changing models, the drivers' aggressiveness have not been considered or it has been modelled as a random parameter which assigns to each driver without paying attention to the real driving characteristics of that driver.

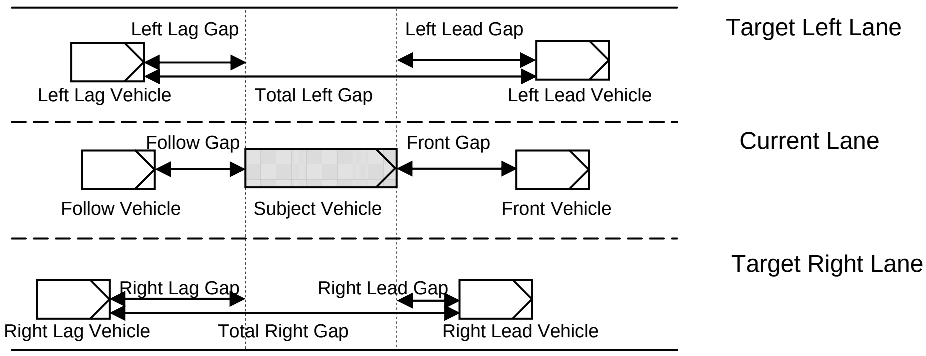

Figure 3: Some important parameters in lane changing manoeuvre.

4 Conclusion

Some of the important previous studies on lane changing behaviour were summarized in this paper. Reviewing the literature, there are many limitations in the existing lane changing behavioural models. Therefore, it is important to propose a new framework for lane changing behaviour of heavy vehicles based on the limitations of the previous studies. The proposed framework considers the following steps:

- Investigate the lane changing characteristics of heavy vehicles,
  Lane changing characteristics of heavy vehicles include: the effects of heavy vehicle lane changing on surrounding traffic, fundamental variables in lane changing behaviour of heavy vehicles and the differences in lane changing behaviour of heavy vehicles and passenger cars.
- Develop a model for lane changing behaviour of heavy vehicles,
  The lane changing model will consider operational and tactical lane changing patterns of heavy vehicles.
- Calibrate and validate the developed models.

This work presented a framework for modelling lane changing behaviour of heavy vehicles. It is believed that the present framework would overcome the limitations of existing lane changing models by developing a specific lane changing model for heavy vehicles.

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