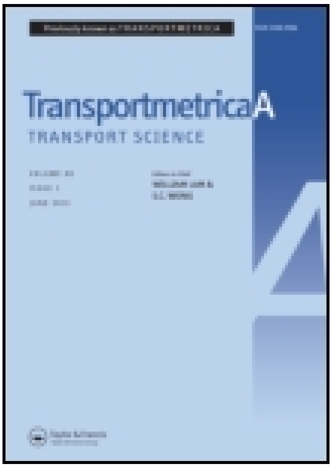

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Modelling driving decisions: a latent plan approach

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Modelling driving decisions: a latent plan approach

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Microscopic traffic simulation tools are becoming increasingly popular in evaluating transport options. Driving behaviour models (e.g. route choice models, lane-changing models, etc.) are essential components of these tools. The state-of-the-art driving behaviour models assume that drivers make instantaneous decisions. However, in reality, many of the driving decisions are based on a specific plan. The plan is however unobserved or latent and only the manifestations of the plan through actions are observed. Examples include selection of a target lane before execution of the lane change, choice of a merging tactic before execution of the merge. Ignoring the effect of plans in the decision framework can lead to incorrect representation of congestion in traffic simulation tools. In this article, we present a modelling methodology to address the effects of unobserved plans in the decisions of the drivers. The actions of the driver are conditional on the current plan and can be influenced by anticipation of downstream traffic conditions. The heterogeneity in decision making and planning capabilities of drivers are explicitly addressed. The methodology has been applied in developing lane-changing behaviour models with disaggregate trajectory data extracted from video recordings of an urban road using the maximum likelihood technique. Estimation results show that the latent plan models have a significantly better goodness-of-fit compared to the 'reduced form' models where the latent plans are ignored. The latent plan models were also found to outperform the reduced form models in validation case studies within the microscopic traffic simulator MITSIMLab.

Keywords: driving behaviour; lane-changing; traffic simulation; latent plan

1. Introduction

Microscopic traffic simulation tools, which mimic individual drivers to deduce real world traffic situations, are ideal tools to analyse and test different congestion management strategies in a controlled environment. These tools analyse traffic phenomena through explicit and detailed representation of the behaviour of individual drivers. Driving behaviour models are thus an important component of the microscopic traffic simulation tools. These models include route choice models, speed/acceleration models and lane changing models. Speed/acceleration models describe the movements in the longitudinal

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direction and lane changing models describe drivers' lane selection and gap acceptance behaviours.

Driving decisions are influenced by a wide range of factors. These include neighbourhood conditions, features of the vehicle and characteristics of the driver, attributes of the network, overall traffic situation, etc. Therefore, in the same network, drivers can behave differently in different traffic situations. In particular, the level of congestion can have a significant impact on driving decisions (Toledo 2007). For example, in heavily congested situations, there can be significant cooperation among the drivers; they are likely to be more alert and conscious about their actions, and their driving decisions can involve substantial planning and anticipation (Hidas 2002, 2005). Though there has been significant research on the effects of neighbourhood conditions on the decisions of the driver (e.g. Gipps 1986, Hunt and Lyons 1994, Yang and Koutsopoulos 1996, Hidas and Behbahanizadeh 1999, Zhang *et al.* 1998, Ahmed 1999, Toledo 2002, etc.), in most cases the models do not adequately capture the sophistication of driver behaviour and the causal mechanism behind their observed decisions (Toledo 2007). Specifically, the existing models represent instantaneous decision-making and assume drivers to be myopic. These shortcomings are more evident in congested and incident affected scenarios where the observed driving behaviour is actually the result of a conscious planning process. These plans may evolve dynamically and an initially chosen plan may not be executed in the end. The plans are therefore unobserved and only the actions (e.g. manoeuvres like acceleration, lane changes, route choice, etc.) are observed. The behavioural predictions based only on myopic considerations are therefore bound to contain significant noise as a result of the models' structural inability to uncover underlying causal mechanisms. Implementation of these models in traffic micro-simulation tools can lead to unrealistic traffic flow characteristics: underestimation of bottleneck capacities and incorrect representation of congestion (Abdulhai *et al.* 1999, DYMO 1999). This was reflected in the findings of the Next Generation Simulation (NGSIM) study on Identification and Prioritisation of Core Algorithm Categories where congested, oversaturated and flow breakdown scenarios have been identified by the users as weak points of traffic micro-simulation tools (Alexiadis *et al.* 2004). Using these tools to evaluate congestion management planning and policy scenarios can result in bias in the analysis.

This article presents a new methodology that explicitly models the choice of plans and effects of these unobserved plans in the observed decisions of the drivers. The models therefore better capture the complexity of human decision making and represent the driving behaviour models in a more realistic manner. The organisation of this article is as follows: first, we present the framework of the latent plan model and the methodology for model development. The methodology is then demonstrated using a case study that is presented next. The summary of the findings and the directions of future research are presented in the concluding section.

2. Methodology

2.1. *Planning in driving decisions*

According to the Next Generation Simulation Models (NGSIM) Core Algorithm Analysis Report (Hranac *et al.* 2004), travel decisions can be classified into the following categories

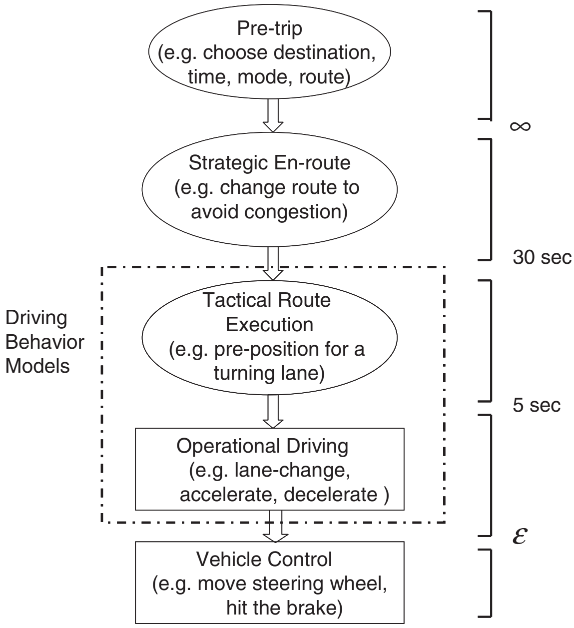

Figure 1. Classification of traveller behavioural algorithms (adapted from Hranac *et al.* (2004), unobserved decisions are shown in ovals).

based on the time scale of application (shown in Figure 1). The pre-trip traveller decisions are the strategic decisions taken before starting a trip and constitute the pre-trip plan of the traveller (e.g. departure time, destination, mode, route, etc.). These may be updated en-route based on network conditions, acquisition of new information, etc. While executing a route from an origin to a destination, a series of tactical manoeuvres are performed by drivers based on sub-goals generated from a variety of factors. Examples include, maintaining a desired travel speed, making up lost time from a previous delay, pre-positioning to get into the appropriate lane, etc. These tactical decisions motivate the operational behaviours of travellers include decisions to control their vehicle (e.g. lane shifting, gap acceptance for executing a lane change or for manoeuvre at an unsignalised intersection, acceleration/deceleration, etc.). The vehicle control decisions deal with driver decisions related to controlling the vehicle at a nanoscopic time-scale level, steering the wheel of the vehicle or pressing the accelerator, for example. Driving behaviour models encompass the tactical route execution and operational driving decisions.

It should be noted that only the actions associated with the operational driving decisions and sometimes the vehicle control decisions are observed. The strategic and tactical plans that lead to that action are generally unobserved or latent.

A general framework of the driving behaviour model is presented in Figure 2. As seen in the figure, in the initial position, the driver makes a plan: for example, selecting a target lane. Depending on the traffic situation and the driver characteristics, the plan can consist of various additional levels: the choice of target gap, the choice of tactic for execution of the lane change, choice of gaps for making a passing manoeuvre, etc. The choice of action

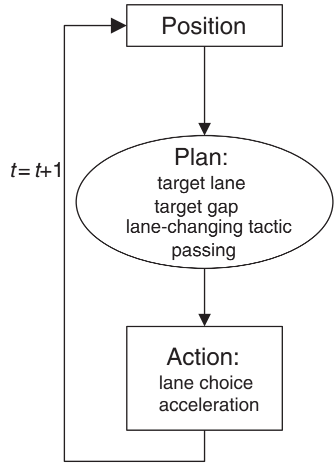

Figure 2. General framework of driving behaviour.

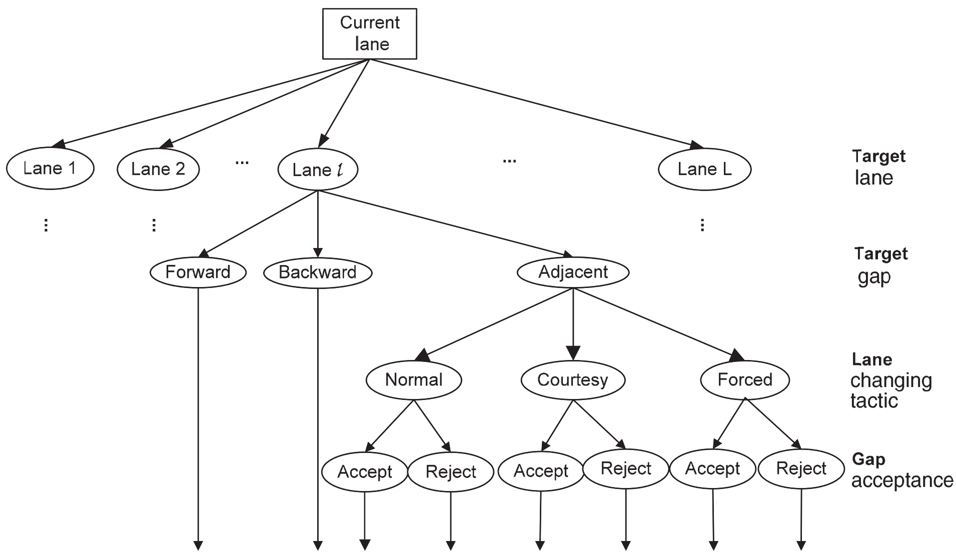

Figure 3. Framework of choice of plan.

depends on the choice of plan and consists of lane choice and acceleration decisions. The chosen action is reflected in the updated position of the driver.

An example of choice of plans of the driver is shown in Figure 3. The pre-trip and en-route strategic plans of the driver (e.g. destination and route choice) may lead to the tactical plan to reach a target lane to take an exit. The subsequent actions of the driver involve looking for an acceptable gap to manoeuvre to the target lane in order to execute the plan. In this process, the driver may also target forward or backward gaps and adjust the acceleration to avail those gaps. In congested situations, where normally acceptable gaps may not be available, the chosen plan can also involve selection of an alternate lane changing tactic (e.g. courtesy or forced gap acceptance). The chosen plan is unobserved and manifests itself through the chosen lane actions and accelerations. However, the plans may be updated due to situational constraints and contextual changes and the observed actions may not be the ones that were originally intended. Failure to change to the target lane, for example, may lead to an observation of no change from the current lane.

Further, the strategic and tactical plans and actions can take place in a dynamic environment where a driver's goals, resulting plans and external conditions are all subject to change. The driver may consider several alternatives to come up with a plan, but the actions that he/she ends up executing might be different from those initially planned. This evolution in plans could be due to several factors. First, situational constraints or contextual changes might lead to revision of the plan. For example, an unusual level of congestion might lead a driver to revise the planned time of travel or route. Or non-cooperation of a driver in the target lane may lead to reevaluation of the lane changing tactic to that lane. Second, the driver's current plans are influenced by the past experiences so that as the history evolves, the plan can also evolve. For example, the choice of an action with an unfavourable outcome might lead one to abandon the plan that led to this action in future choice situations. Third, drivers might eventually adapt to conditions in their environment so that they might exhibit inertia in the choice of their plans and actions. For instance, drivers may have a preference to stay in the current lane.

There can be considerable difference in aggressiveness, driving skills, intelligence and planning ability of drivers. Drivers may also have different levels of familiarity with the network. These driver-specific characteristics (generally unobserved) can have a significant impact on the latent plans.

2.2. *Formulation*

The key features of the latent plan model are as follows:

(1) Individuals choose among distinct plans (target/tactic). Their subsequent decisions are based on these choices. The chosen plans and intermediate choices are latent or unobserved and only the final actions (manoeuvres) are observed.
(2) Both the choice of plan and the choice of action conditional on the plan can be based on the theory of utility maximisation. The interdependencies and causal relationships between the successive decisions of an individual result in serial correlation among the observations.
(3) The observed actions of the individuals depend on their latent plans. The utility of actions and the choice set of alternatives may differ depending on the chosen plan.
(4) The choice of the plan at a particular time may depend on previous plans. For example, persistence and inertia effects may affect the choice whether or not to continue to follow the original plan or to shift to an alternative one. Thus, the choice of plans can lead to state-dependence in the decision process.
(5) The current plan can also depend on anticipated future conditions and may include expected maximum utility (EMU) derived from the decisions involved with the execution of the plan.

In the following subsections, we present the basic latent plan model that is applicable for cases without state-dependence (only serial correlation). These include situations involving one-time decisions, as well as panel observations where the subsequent choices of plans (conditional on individual-specific characteristics) are independent. The basic model can be extended to explicitly capture the state-dependence between subsequent plans and actions (which has been presented in Choudhury *et al.* (2010)).

The proposed framework addresses the serial correlation among the decisions of the individual across time and choice dimensions but do not address the state-dependence among subsequent plans. That is, conditional on individual-specific characteristics, the successive plans of individuals are assumed to be independent. The overall model framework is presented in Figure 4. Variables or choices in rectangles are observable, while those in ovals are unobservable or latent.

The plan of an individual n at any instant t (l_{nt}) is influenced by explanatory variables and individual-specific characteristics. The attributes of the alternatives (X_{nt}) are generally observed but the individual-specific characteristics associated with the individual (υ_n) are generally unobserved or latent and capture the serial correlation among the decisions of the same driver. For example, in the case of lane selection behaviour, attributes of the alternatives (target lanes) like average speed, density, lead and lag vehicle characteristics, etc., are observed and driver characteristics like aggressiveness, driving skills, planning horizon, etc., are latent. These latent variables can be discrete or continuous. Characteristics of the driver such as planning capability, for example, can be represented by discrete classes of drivers (e.g. drivers who plan-ahead and drivers who do not). Continuous latent variables include attitudes, perceptions and personality traits of the individual (e.g. impatience, aggressiveness, planning horizon, etc.). The actions of the individuals depend on the chosen plan as well as the observed and latent explanatory variables. These individual specific variables remain the same for all decisions of the same individual across time and choice dimensions (agent effect). However, it is assumed that actions (j_n) and plans (l_n) of individual n (conditional on υ_n) are independent over time. This assumption is relaxed in Choudhury *et al.* (2010) where a Hidden Markov Model

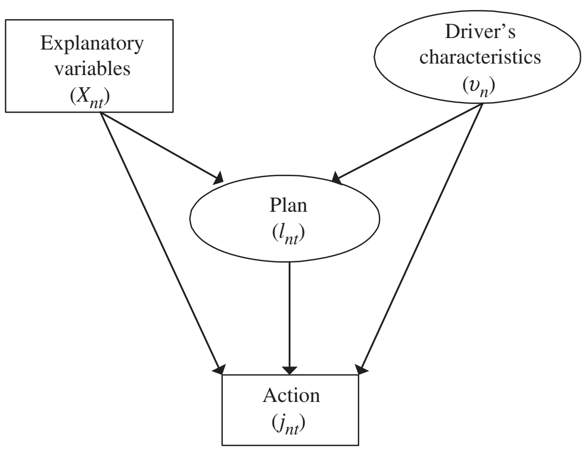

Figure 4. Latent plan model without state-dependence.

(HMM)-based formulation is used for capturing the effects of the past decisions in the current plan of the driver.

The general model framework is presented in Figure 5. This framework consists of two levels: choice of plan and choice of action conditional on the plan. The selection of the plan (indexed by l) in the upper level drives the selection of an action (indexed by j). The action choice sets and corresponding utilities, shown in the lower level, may vary depending on the plan.

The trajectory of an individual includes a series of observed actions. For driving behaviour models, this corresponds to a series of lane actions and acceleration decisions of the driver.

Let,

$P_n(l_t|\upsilon_n)$ probability of individual n selecting plan l at time t conditional on individual-specific characteristics
$P_n(j_t|l_t,\upsilon_n)$ probability of individual n selecting action j at time t given plan l conditional on individual-specific characteristics
$P_n(j_t|\upsilon_n)$ probability of action j by individual n at time t conditional on individual-specific characteristics
L_n the set of plans in the choice set of individual n
T_n number of consecutive observations of individual n

At time t for individual n, the probability of observing a particular action j is the sum of probabilities that he/she is observed to execute action j given that the selected plan is l, over all plans in the choice set of the individual.

$$P_n(j_t|\upsilon_n) = \sum_{l \in L_n} P_n(j_t|l_t, \upsilon_n) P_n(l_t|\upsilon_n) \tag{1}$$

Assuming that actions (j_n) and plans (l_n) of individual n (conditional on υ_n) are independent over time (relaxed in the next section), the probability of observing his/her sequence of decisions can be expressed as follows:

$$P_n\big(j_1, j_2, \ldots, j_{T_n}|\upsilon\big) = \prod_{t=1}^{T_n} \sum_{l=1}^{L_n} P_n(j_t|l_t, \upsilon_n) P_n(l_t|\upsilon_n) \tag{2}$$

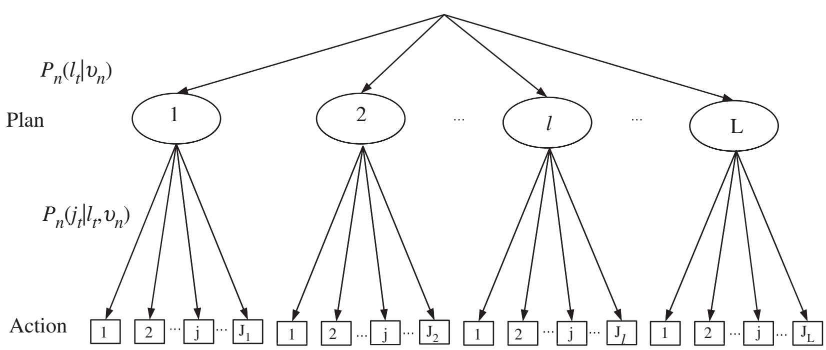

Figure 5. Basic model framework.

The unconditional choice probabilities of observing the sequence of decisions by individual n are given by the following equation:

$$P_n(j_1, j_2, \ldots, j_T) = \int_{\upsilon} P_n\big(j_1, j_2, \ldots, j_{T_n} | \upsilon\big) f(\upsilon) \mathrm{d}\upsilon \tag{3}$$

where $f(\upsilon)$ is the distribution of the individual-specific random term (e.g. aggressiveness).

It may be noted that, structurally, the latent plan models have similarities with the Latent Class Choice Model (LCCM) where the factors 'generating' the heterogeneity among individuals can be conceptualised as discrete or categorical constructs (Kamakura and Russell 1989, Gopinath 1995). However, the class-membership models are based only on characteristics of the individuals and not on other variables that influence their attitude. The membership of an individual in a class is thus static and do not change over time with change in situations. The latent plan models, on the other hand, are estimated with panel data and the unobserved factor (the latent plan) can vary dynamically with change in situation based on neighbourhood variables. The latent plan models thus have a more flexible structure and can therefore be inferred as an extension of LCCM that is applicable in a dynamic case.

2.3. *Specification*

The probabilities of choice of plan and action can be calculated using a utility-based choice framework. The specifications of these utilities are discussed below.

2.3.1. *Choice of plan*

The choice of a plan can be based on utility maximisation and may include EMU derived from the decisions involved with executing that plan. The utility of latent plan l for individual n at time t can be expressed as follows:

$$\begin{aligned} U_{lnt} &= U(X_{lnt}, I_{lnt}, \upsilon_n, \varepsilon_{lnt}) \\ I_{lnt} &= \mathrm{E}\big(\max\big(\mathrm{U}_{1\,lnt}, \mathrm{U}_{2\,lnt}, \ldots, \mathrm{U}_{j\,lnt}, \ldots, \mathrm{U}_{J_l\,lnt}\big)\big) \end{aligned} \tag{4}$$

X_{lnt} attributes of plan l for individual n at time t, a subset of X_{nt}
I_{lnt} EMU from actions associated with plan l of individual n at time t
U_{jlnt} utility of action j under plan l to individual n at time t
υ_n individual-specific random effect
ε_{lnt} random utility component of plan l for individual n at time t

2.3.2. *Choice of action*

The observed choices/actions depend on the chosen plan. The choice set, as well as the functional form of the utility of an action j may vary depending on the chosen plan. The utility of action j under plan l can be expressed as follows:

$$U_{jlnt} = U\big(X_{jlnt}, \upsilon_n, \varepsilon_{jlnt}\big) \tag{5}$$

where,

X_{jint} atttributes of action j and plan l at time t, a subset of X_{nt}
υ_n individual-specific random effect
ε_{jlnt} random utility component of action j and plan l at time t

The conditional probabilities of selecting plan ($P_n(l_t|\upsilon_n)$) and action ($P_n(j_t|l_t, \upsilon_n)$) are based on the utilities discussed above (U_{lnt} and U_{jlnt}, respectively). The specification of the probabilities will depend on the assumptions made regarding the distribution of the random utility components of U_{lnt} and U_{jlnt}. For example, if the random components are independently and identically extreme value distributed, then the kernel of the choice model will be logit. It may be noted that strong correlations between systematic and random (ε_{lnt} and ε_{jlnt}) components of plan and action levels may lead to identification problems. This makes the latent plan models applicable only to situations where such strong correlations are not present.

The strategic and tactical choices comprising the latent plans can also be influenced by the geometric and traffic attributes. The effect of latent path-plan, for example, may be more evident in an urban arterial with closely spaced turns compared to a freeway network where exits are far apart. Similarly, there can be higher propensity to target a distant lane if there is a large difference in the level of service (LOS) among different lanes. Again, the underlying plan for executing a lane change in a congested freeway can differ significantly from the choice of plan in an uncongested situation where acceptable gaps are readily available.

2.4. *Model development*

The latent plan model framework presented in the previous sections were developed using the process shown in Figure 6, which involves using both disaggregate and aggregate data. Disaggregate data, which are detailed vehicle trajectories at a high-time resolution are used in the model estimation phase. In this phase the model is specified and explanatory variables, such as speeds and relations between the subject vehicle and other vehicles, are generated from the vehicle coordinates extracted from the trajectory data. The model parameters are estimated using a maximum likelihood technique to match the observed lane changes that occurred in the trajectory data. This estimation approach does not involve the use of any traffic simulator, and hence the estimated models are simulator independent.

In order to demonstrate the benefits that may be derived from using the modified models, they must be validated and demonstrated within a microscopic traffic simulator that incorporates not only the lane changing models being studied, but also other driving behaviour models, such as acceleration models. Therefore, the estimated model needs to be implemented within a microscopic traffic simulator. MITSIMLab (Yang and Koutsopoulos 1996) was used in all the cases described in this article. In the validation case studies, aggregate data, which are significantly cheaper to collect and in many cases readily available, may be used. Part of the aggregate dataset is first used to adjust key parameters in the lane changing model as well as parameters of other behaviour models and to estimate the travel demand on the case study network. This aggregate calibration problem is formulated as an optimisation problem, which seeks to minimise a function of the deviation of the simulated traffic measurements from the observed measurements and

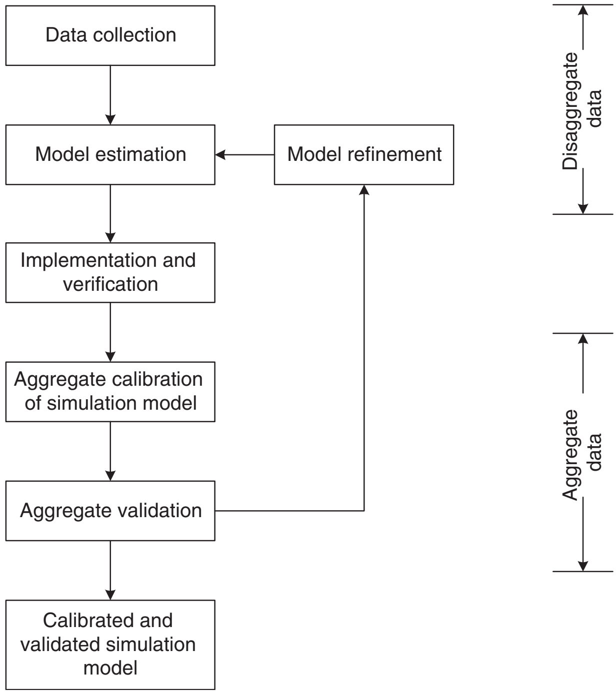

Figure 6. Estimation, calibration and validation process.

of the deviation of calibrated values from their *a priori* estimates, if available (Ben-Akiva *et al*. 2003, Toledo and Koutsopoulos 2004). The rest of the data is used for the validation itself, which is based on comparison of measures of performances that may be calculated from the available with corresponding values from the simulator, such as sensor speeds and flows, the distribution of vehicles among the lanes, amount and locations of lane changes.

3. Case study: lane choice in an urban intersection

As mentioned in the previous sections, the effects of plans in observed manoeuvres are more prominent in certain traffic scenarios (e.g. in high level of congestion, in the presence of closely spaced turns, work zones, incident spots, etc.). The case study presented below demonstrates the effects of including the latent plans in the decision framework using the lane selection behaviour in an urban intersection. In this article, we highlight the methodological aspects of the model and the comparison results with a ‘reduced form’ model to show the improvements in the goodness-of-fit and prediction capability after inclusion of the latent plans. More details of the model formulation, estimation and validation results have been presented in Toledo *et al.* (2005), Choudhury and Ben-Akiva (2008) and Choudhury *et al*. (2008).

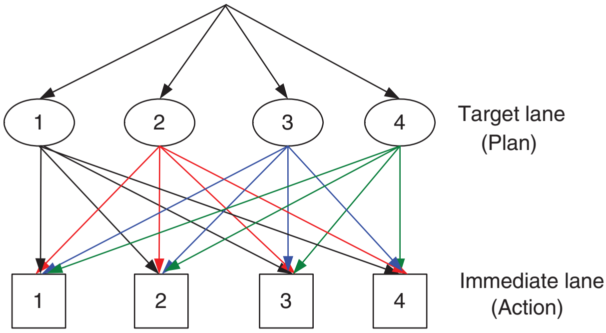

Figure 7. Structure of the intersection lane selection model.

3.1. *Background*

Arterial corridors have a set of varied driving activities that differ by lane and location. These activities encompass trip destination activities (parking, entering transit stops, right turns, left turns, etc.), trip origination activities (exiting a parking spot, exiting transit stops, etc.) and complex routing behaviours (permissive left turns, pedestrian-impeded right turns, etc.). Drivers familiar with the network may be aware of these activities and be mindful about how these vary by lane and location. While turning at intersections, these drivers tend to make appropriate tactical lane positioning decisions to minimise their travel times and driving efforts. Due to situational constraints, immediate execution of the tactical lane selection plan may not be possible. For example, at a particular instant, conflicts with other vehicles can delay movement to the target lane. Further, changes in circumstances may lead to changes in the tactical plan: a long queue build-up in the chosen target lane, for example, can lead to amendment to the original target. The chosen target lanes are thus unobserved and only the immediate choice of lanes is observed.

A lane selection model has been developed for urban intersections, which explicitly takes into account the tactical pre-positioning of drivers approaching the arterial mainline from side streets was developed in this regard. The familiarity and planning ability of the drivers, that is: how far they 'look-ahead' or 'plan-ahead' affect their tactical plans was explicitly taken into account.

3.2. *Model structure*

The intersection lane selection is therefore a two level decision:

- Choice of target lane (plan)
- Choice of immediate lane (action)

The choice of target lane is a tactical decision of the driver whereas the choice of immediate lane is governed by manoeuvrability considerations. The framework of the model is shown in Figure 7. Latent choices are shown as ovals and observed ones are shown as rectangles.

At the first level, the driver chooses the most desirable lane as the target lane. The target lane choice set constitutes all the available lanes the driver is eligible to move to.

The target lane utilities are affected by a wide range of factors. These include factors related to path-plan considerations, such as the distance to a point where the driver needs to be in specific lanes and the number of lane changes required from the target lane to the correct lanes. The effects of path-plan in the target lane choice can also depend on the planning capability of the driver and his/her familiarity with the network. Drivers who are familiar with the network and 'plan-ahead' are likely to pre-position themselves in the correct lanes well-ahead of the section prior to the turn. These drivers may also be aware of the lane-specific obstructions in downstream sections and take into account the anticipated delays associated with staying in a lane while making their lane choices. On the other hand, drivers who are not familiar with the network and/or do not plan-ahead are not likely to be affected by path-plan considerations or anticipated delay beyond their immediate sections.

Depending on the planning capability, the drivers can thus belong to either of the two classes:

- Class 1: Myopic drivers. Drivers who consider the path-plan and anticipated delay only in their immediate subsequent section while making the lane selections.
- Class 2: Drivers who plan-ahead. These drivers consider path-plan and anticipated delay beyond their immediate subsequent section while making the lane selections.

The perspectives of the two classes of driver are presented in Figure 8(a) and (b). Parameters associated with the target lane of the driver may be class-specific as well, indicating significant difference in sensitivity to influencing variables among driver classes.

Given the choice of the target lane, the driver selects the immediate lane. The immediate lane selection depends on the choice of target lane but is also influenced by manoeuvrability considerations. For example, a lane may be unavailable as an immediate lane if it is already full. To make the model more flexible, the choice set for the immediate lane is assumed to include all available lanes in the roadway irrespective of the target lane and the current position of the driver. The structure can thus accommodate cases when the target lane and lanes in the direction of the target lane are blocked by other vehicles and the driver has no option but to move to a different connecting lane. This extreme situation is illustrated in Figure 9 with a hypothetical example where the target lane of the driver is Lane 2 (the path to which is blocked) and the driver chooses Lane 4 as the immediate lane. The other option for the driver is to wait till the vehicles in Lane 3 move forward and manoeuvre to Lane 2 when possible. The immediate lane choice is thus affected by manoeuvrability considerations, the driving effort needed to reach a particular lane and is conditional on the choice of target lane.

3.3. *Data*

The intersection lane choice model has been estimated from data collected from Lankershim Boulevard in Los Angeles, California. Vehicle trajectory data was collected in 2005 from a segment of the arterial located near the intersection with US highway 101 as part of the FHWA's NGSIM project. The dataset used for estimating the intersection lane choice model includes 703 observations (1 observation per vehicle). 629 of them are

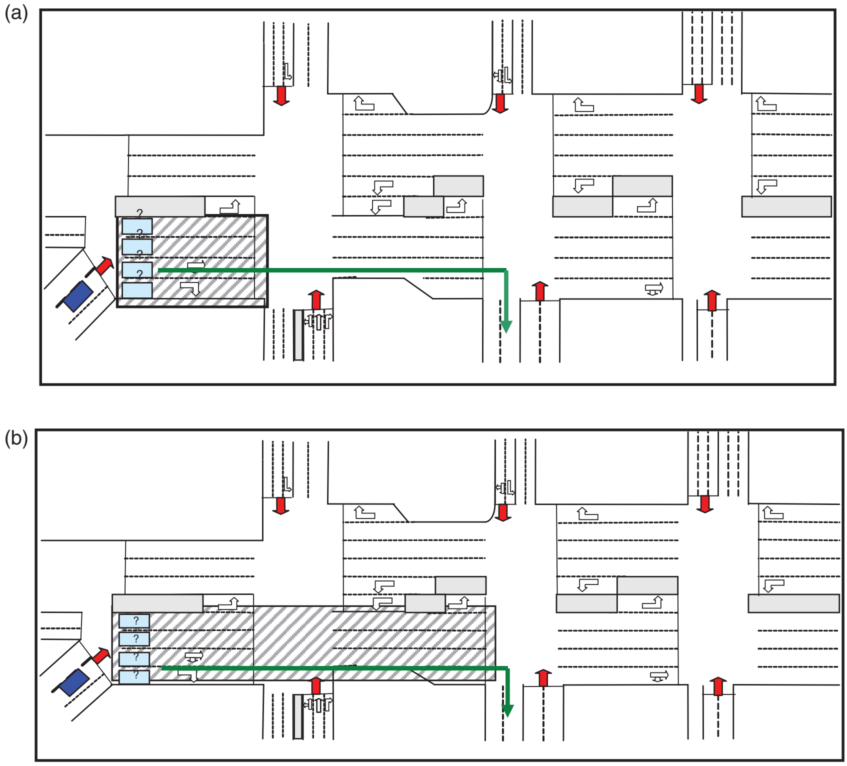

Figure 8. Structure of the intersection lane selection model. (a) Perspective of myopic drivers and (b) perspective of drivers who plan-ahead.

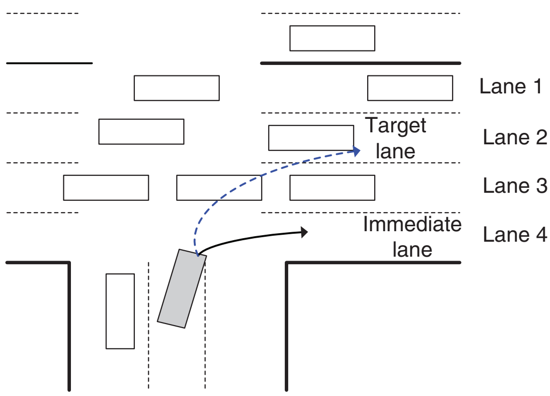

Figure 9. Example of a situation when the target lane is blocked.

northbound and 74 of them are southbound. Out of these vehicles, 269 (38.1%) turn to closest receiving lanes, 435 (61.9%) later change to different lanes within the section. The majority of the entering vehicles are observed for more than one sections (80.2%) with more than half (55.9%) vehicles are observed for more than two sections.

Table 1. Estimation results.

Final log-likelihood		−2115.8	
Initial log-likelihood		−2797.9	
Number of model parameters		20	
Variable		Parameter	*t*-Statistics
Target lane			
Lane 2 constant		−0.837	−3.64
Lane 3 constant		1.30	7.62
Lane 4 constant		3.25	8.16
Anticipated delay (second)		−0.477	−0.56
Lanes away from turning lane (myopic)	Coefficient – myopic drivers	−0.0240	−0.63
	Constant – myopic drivers	1.43	0.83
	Heterogeneity coefficient – myopic drivers	1.53	0.75
Lanes away from turning lane (with plan-ahead)	Coefficient – drivers who plan-ahead	−4.08	−1.98
	Constant – drivers who plan-ahead	2.05	3.01
	Heterogeneity coefficient – drivers who plan-ahead	0.466	0.74
EMU from immediate lane		0.915	7.22
Driver class			
Driver population with >1 section plan-ahead (%)		18.3	2.07
Immediate lane			
Lanes away from connecting lane	Coefficient	−1.01	−1.19
	Constant	0.691	1.94
	Heterogeneity coefficient	1.96	3.48
Target lane dummy		3.16	4.54
Lanes away from target lane	Coefficient	−4.42	−3.00
	Constant	2.12	2.14
	Heterogeneity coefficient	0.0904	0.36
Conflict dummy		−1.76	−9.63

3.4. *Results*

The model formulation was similar to the general latent plan formulation presented in Equations (1)–(5) but with an additional complexity of the presence of latent classes (as supported by the data, see Choudhury and Ben-Akiva (2008) for details). All components of the model (target lane choice, immediate lane choice, driver class membership) were estimated jointly using a maximum likelihood estimation procedure as described in the previous section. The estimation results are presented in Table 1.

3.4.1. *Choice of target lane (plan)*

The target lane choice model describes drivers' choice of lane they would want to travel in. The target lane choice of the driver is affected by the path-plan, the lane attributes and driver characteristics. Path-plan variables include number of lanes a driver has to cross (if any) in order to take a turn or exit while following the path. Lane attributes include queue length, queue discharge rate, average speed, etc., of each lane. In this model, the queue length and queue discharge rates are combined in a single variable anticipated delay.

This variable represents the delay associated with the queue in time unit and is calculated by dividing the current queue length by the average queue discharge rate in that lane. The variables affecting the immediate lane choice also have an indirect effect on target lane choice. This has been captured through EMU variables.

The magnitudes of the lane-specific constants indicate that all else being equal, the drivers prefer lanes on the right (the rightmost lane being the most preferred lane). It should be noted that though the model has been developed with data where the receiving section had 3 or 4 lanes, the model structure is flexible enough to be applied to other scenarios with a different number of available lanes. For this, the lane constants in particular need to be re-calibrated.

As described in the earlier section, a latent class formulation has been used for the model to capture the heterogeneity in planning capability of drivers. The probability of the driver being a myopic driver (Class 1) or a driver who plans ahead (Class 2) is calculated along with the other model parameters. The estimated probability that the driver belongs to Class 2 was found to be 18.3%.

The influencing variables differ depending upon the plan-ahead distance of the driver. For example, drivers who are familiar with the network and plan ahead may consider the anticipated delay in subsequent sections while selecting their target lanes. Therefore, an anticipated delay value was calculated for each class of driver based on what segments they are considering while making the choices. The functional form of the anticipated delay variable can be expressed as follows:

$$\begin{aligned} \tilde{q}_{nt}^{kl} &= \frac{1}{1+\exp(-q_{nt}^{kl})} \quad k=1,2 \\ q_{nt}^{1l} &= d_{nt}^{1l}/r_n^{1l}, \quad q_{nt}^{2l} = q_{nt}^{1l} + d_{nt}^{2l}/r_n^{2l} \end{aligned} \tag{6}$$

where

- q_{nt}^{kl} anticipated delay in lane l considering k sections ahead
- d_{nt}^{ki} queue length in lane i in section k at time t
- r_{nt}^{ki} average queue discharge rate of lane i in section k (vehicles s^{-1})

The anticipated delay has a diminishing effect on the utility of target lane and the sensitivity to anticipated delay was found to be significantly different for the two classes of drivers.

The path-plan of the driver has an important role in the target lane selection. The two classes of drivers are found to have different sensitivities to path-plan considerations, which in this case has been modelled as an interaction between the number of lanes away from the correct lane and the aggressiveness of the driver. The functional form best fitting the data is found to be as follows:

$$\left[\frac{\theta_1}{\psi_1+\alpha_1\upsilon_n}\left(e_n^{1l}\right)(1-\delta_n)+\frac{\theta_2}{\psi_2+\alpha_2\upsilon_n}\left(e_n^{2l}\right)\delta_n\right] \tag{7}$$

where

- δ_n 1 if the driver plans-ahead beyond the immediate section
- e_n^{1l} lanes away from turning lane for myopic drivers

e_n^{2l}	lanes away from turning lane for drivers who plan-ahead
$\theta_i, \psi_i, \alpha_i$	of vehicle class i

As seen from the estimates, for both classes of drivers, utility of lanes reduce if they are away from the lane that the driver needs to be in to follow his path. This disutility is, however, less for aggressive drivers, since they are more prone to make aggressive lane changes later if needed (inertia effect is dominant). The disutility was found to be larger and more significant for drivers who plan ahead (Class 2).

The EMU term captures the maximum utility that can be derived from selecting a particular lane as the immediate lane. It has a significant effect on the target lane choice. The EMU can be calculated as the logsum of the immediate lanes given the target lane (Ben-Akiva 1974, Ben-Akiva and Lerman 1985). Mathematically, this refers to the following:

$$\begin{aligned} EMU_{ln} &= E(\max(U_{1\,ln}, U_{2\,ln}, \ldots, U_{j\,ln}, \ldots, U_{J_1\,ln},)) \\ &= ln(\exp(V_{1\,ln}) + \exp(V_{2\,ln}) + \cdots + \exp(V_{j\,ln}) + \cdots + \exp(V_{J_1\,ln})) \end{aligned} \tag{8}$$

where

EMU_{ln}	expected maximum utility derived by individual n from lane l
U_{jln}	utility of immediate lane j for driver n given target lane l

The estimated utility of the target lane can thus be expressed as follows:

$$\begin{aligned} U_{ln} = \beta_l - 0.477\big[(\tilde{q}^1_{ln})(1-\delta_n) + (\tilde{q}^2_{ln})(\delta_n)\big] - \frac{0.024}{1.43 + 1.53\upsilon_n}(e^1_{ln})(1-\delta_n) \\ - \frac{4.08}{2.05 + 0.466\upsilon_n}(e^2_{ln})\delta_n + 0.915(EMU_{ln}) \end{aligned} \tag{9}$$

where

β_l	constant for lane l
$\bar{q}^1_{ln}$	anticipated delay function in lane l for myopic drivers
$\bar{q}^2_{ln}$	anticipated delay function in lane l for drivers who plan-ahead
e^1_{ln}	lanes away from correct lane for myopic drivers
e^2_{ln}	lanes away from correct lane for drivers who plan-ahead (consider path-plan beyond current section)
EMU_{ln}	expected maximum utility derived by driver n from selecting lane l as target lane
δ_n	1 if the driver plans ahead beyond immediate section

3.4.2. *Choice of immediate lane (action)*

As seen in Table 1, immediate lane choices were found to be influenced by manoeuvrability considerations and inertia to continue to the naturally connecting lane. Inertia effects are captured by variables like current lane inertia and number of lanes away from the connecting lane. The inertia effect was greater for aggressive drivers. Aggressive drivers tend to stay in their current lane as long as possible and then make aggressive changes if a

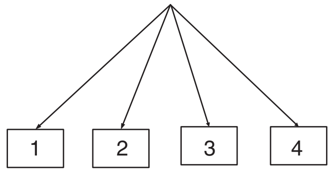

Figure 10. Reduced form model structure (with no latent plan).

lane change is warranted by the path-plan. Drivers were also found to have a strong preference to reach their target lane and lanes closer to their target lanes.

Manoeuvre to a given lane may not be possible due to conflicts with neighbouring vehicles. In the case of such obstructions or conflicts, the driver can choose an immediately available lane, or can wait until the neighbouring vehicle moves and there are no obstructions to manoeuvre to the intended target lane. As a result, if there are conflicting vehicles in the direction of a lane, the driver was found to have a lower preference for that lane.

The utility of immediate lane j is summarised in the following equation:

$$U_{jn} = -\frac{1.01}{0.691 + 1.96\upsilon_n}(c_{jn}) + 3.16(l_{jn} = 0) - \frac{4.42}{2.12 + .0904\upsilon_n}(l_{jn}) - 1.76\gamma_{jn} \qquad (10)$$

where

- c_{jn} lanes away from connecting lane
- l_{jn} lanes away from target lane l, $l \in L_n$
- γ_{jn} 1 if manoeuvre to lane j is obstructed by an adjacent vehicle (conflict dummy)

3.5. *Model comparison*

The improvement in the goodness-of-fit of the new model was statistically compared with a 'reduced form' model estimated with the same data. The reduced form model is a single level lane choice model with similar variables but no latent target lanes (presented in Figure 10, detailed in Choudhury and Ben-Akiva (2008)).

The models have been compared using tests for comparing non-nested models: Akaike Information Criteria (AIC) (Akaike 1974) and adjusted rho-bar square. These statistics discount for the larger number of parameters in the model with target lane level. The results are presented in Table 2.

The model with explicit target lane choice has improved likelihood values compared to the single-level model. It also has larger values both in terms of AIC and $\bar{\rho}^2$, which indicates that it better fits the data, and therefore should be selected for prediction.

The new lane-changing model was implemented in the microscopic traffic simulation model, MITSIMLab (Yang and Koutsopoulos 1996) and tested for validation by comparing against field observations. Because of unavailability of other suitable processed datasets, the aggregate data from the same site (Lankershim Boulevard, CA) has been used for preliminary model validation. The Lankershim trajectory data was aggregated to

Table 2. Comparison of goodness-of-fit.

Statistic	Reduced from (R)	Latent plan (U)
Likelihood value	−2120.4	−2115.8
Number of parameters (K)	19	20
Akaike information criteria (AIC)	−2139.3	−2135.8
Adjusted rho-bar square ($\overline{\rho}^2$)	0.235	0.237

generate synthetic sensor counts and speeds that are used for validation. Exact vehicle O–D flows were calculated from the trajectory data and so no route choice was involved. Aggregate calibration was performed first with part of the data (8:28 am to 8:50 am) to adjust the driving behaviour parameters of other components of MITSIMLab. Sensor data from 8:50 am to 9:00 am in the north bound direction (not used for aggregate calibration) was used for validation.

Comparison among the observed data and the simulated outputs from the base MITSIMLab model and the new model are shown in Figure 11. As seen in the diagrams, the lane distributions of the new model have a better fit to the observed data than the base model. Particularly, in the first section (which has the highest volume of vehicles entering from the side streets), the base model overpredicts the through lane occupancies. The new model with target lane choice better captures the vehicle pre-positioning.

4. Conclusion

A latent plan-based modelling approach thus gives a better representation of the decision mechanism by capturing the causal relationships between plans and actions of the driver and results in more realistic traffic simulation. This was demonstrated by a case-study involving lane selection in an urban intersection where the inclusion of the latent plans was justified by comparing goodness-of-fit of estimation and aggregate validation results. The comparison of goodness-of-fit of estimation results exhibited the improvements in model estimates as compared to the reduced form models that do not have any latent mechanism. The aggregate validation results demonstrated this through improvements in the simulation capability in comparison to the state-of-the-art models that use instantaneous decisions of drivers based on myopic considerations.

It may be noted that the model presented in this article can be extended to explicitly capture the state-dependence between subsequent plans and actions (which has been presented in Choudhury *et al.* (2010)) as well as to account for expected utility from future decisions (research on this direction using dynamic programming is currently underway).

The concept of latent plan and the proposed framework has enormous potential both in modelling driving decisions and modelling decisions in other scenarios where the decisions of individuals involve unobserved planning. Examples include route choice models, shopping destination choice, activity participation and travel behaviour models, and many other choice situations involving ‘hidden’ decision layers and latent alternatives.

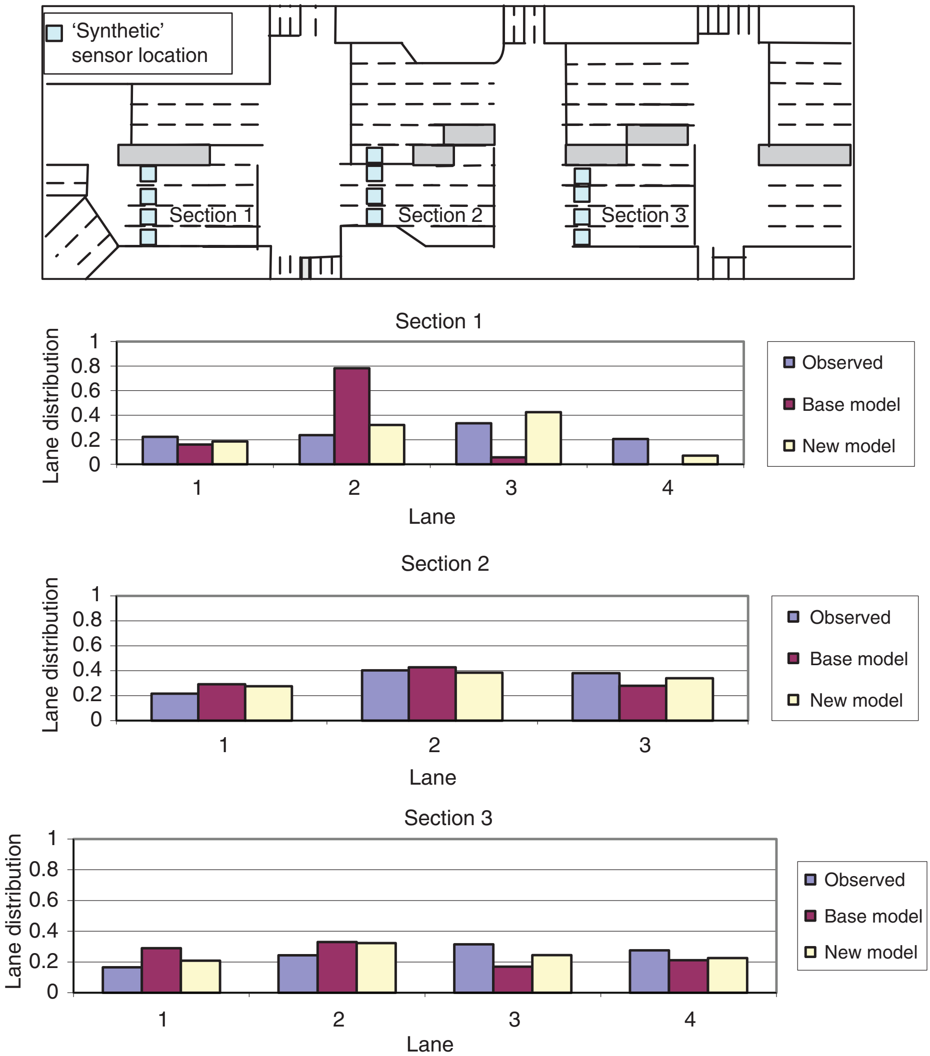

Figure 11. Validation results: lane distributions at the beginning of the arterial mainline.

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