Modelling Individual Behaviour In Microsimulation Models

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1 Introduction

Microscopic traffic simulation models are becoming increasingly important tools in modelling complex transport networks and evaluating various traffic management alternatives that cannot be studied by other analytical methods. These models simulate individual vehicle/driver units as they travel through the network between their origin and destination. The most widely used traffic simulators in Australia are PARAMICS, AIMSUN and VISSIM. While these packages are regarded as the state-of-the-art, several problems were also identified in practice. One issue of concern is the modelling of individual driver behaviour and its effects on the simulation outputs.

The heterogeneity that individual vehicle and driver characteristics represent has an important effect on traffic performance. It is therefore important to reproduce the variability that exists in these behaviours in any real network. This raises problems of calibration and validation of these behavioural attributes in practice as these characteristics are hard to observe and little or no data are available about local conditions.

This paper presents an analysis and comparison of the modelling concepts related to individual driver behaviour in the above 3 simulators, using the following model versions: AIMSUN v4.2, Quadstone (Q-)PARAMICS v4.2, and VISSIM v3.70. It describes the vehicle/driver parameters used in each model and illustrates the effects of some parameters on the output results using small hypothetical case study examples. The paper discusses various options and offers recommendations for surrogate measures that can be used to collect information on such behavioural parameters for the calibration of simulation models. It is important to note that the aim of this analysis is to draw conclusions on how individual driver behaviour modelling can be improved in the next generation of microsimulation models, rather than a general qualitative assessment of the models.

2 Individual attributes

The travel decisions and driving behaviour of individual travellers are highly dependent on the characteristics of the individuals as well as those of the vehicles they drive. As microsimulation models generally represent a vehicle and its driver as one entity, a driver-vehicle unit (DVU) or agent (DVA), these units must possess a combination of both the vehicle's and the driver's individual characteristics. The NGSIM Task D Final Report (Cambridge Systematics, Inc., 2003) provides a good summary of the behavioural attributes of vehicles and travellers.

Vehicle characteristics can be subdivided into vehicle types, physical features and dynamics. While different *vehicle types*, such as cars, trucks, buses etc., are represented by their particular set of physical and dynamic attributes, vehicles having the same physical and dynamic characteristics need to be distinguished due to their other characteristics, eg. emergency, transit or high occupancy vehicles.

Relevant *physical attributes* include: length, width, height, opacity, mass, trailer articulation, passenger capacity. These may have an influence not just on the behaviour of the vehicle's own driver but that of other adjacent vehicles, eg. many drivers try to avoid following a larger vehicle that limits visibility.

Vehicle dynamics can be described by the following factors: maximum acceleration and deceleration, maximum speed and minimum turn radius.

Personal characteristics of the drivers influence the three basic steps of the driving task: perception, decision-making and control. A large variety of human factors may be considered here: visual acuity, impairment, attention, awareness, familiarity with the environment and with the vehicle, skill, emotional state, aggressiveness, impatience, value of time, risk acceptance, propensity for compliance with traffic laws, willingness to cooperate.

Many of these factors are interrelated, overlapping and not directly observable, and it would be impossible and unnecessary to represent all these in a simulation model. However, it is important that the models apply a sufficient range of parameters that can reproduce the realistic variations in traffic flow.

3 Review of behavioural parameters in simulation models

In this section, the parameters and modelling concepts used to represent behavioural differences in the three selected models are reviewed and compared, based on the user manuals (TSS 2003, Quadstone Ltd. 2003, and PTV Ag. 2003) and a study of each simulator. Table 1 provides a summary and comparison of the behavioural parameters available in the models. The parameters are grouped by the driving task/physical attribute they are mainly related to. However, some parameters have an effect on more than one driving task and the tasks themselves are related to each other. For example, acceleration characteristics have an affect on the desired speed, on car following, etc. The table shows the parameter names used in each model and an attempt was made to list parameters with the same function in each model side by side. For each parameter, two character codes are added to indicate the scope and the value type of the parameter.

The *acceleration* (including negative acceleration, i.e. deceleration) *parameters* need to represent a combination of individual vehicle and driver characteristics: the maximum value that a DVU is able and willing to use in an emergency situation (which is not necessarily the physical maximum of the vehicle), and the normal or desired value that is used under standard conditions. VISSIM offers the full range of four separate parameters to represent these values (although in practice the desired acceleration is rarely used, mainly due to lack of valid field data), AIMSUN uses the normal deceleration, while Q-PARAMICS only provides for the maximum values (note that this has changed in version 5.0). All these parameters are assigned to a vehicle type, and the models allow any number of vehicle types to be defined. Thus, individual differences in acceleration characteristics can be modelled appropriately in each model. However, Q-PARAMICS uses a fixed constant value for each parameter, therefore many vehicle types need to be defined to represent the variation of individual behaviour, which, in the other two models can be defined as a distribution (with its mean, minimum-maximum and variance) for one vehicle type.

The *desired speed* that a driver is aiming to use (if there are no other constraints) is a combination of the physical conditions of the vehicle and the road, the personal characteristics of the driver, and the legal speed limit that applies to the road section. AIMSUN uses three parameters to represent this behaviour: the Desired speed is defined as a distribution for each vehicle type, the Speed limit is assigned to each road link, and another vehicle type parameter: Speed acceptance, also defined as a distribution for each vehicle type, represents the driver's willingness to comply with the speed limit. VISSIM also uses Desired speed as a distribution for each vehicle type, but instead of speed limits defined for each link, it uses Desired speed decision points, that can be located at any point on the road network, where vehicle types can be assigned to a different desired speed distribution. VISSIM does not have a parameter equivalent to the Speed acceptance used in AIMSUN, therefore, the Desired Speed distributions must be defined so that they represent the propensity of drivers to respect the speed limits. In Q-PARAMICS the vehicle types have a fix maximum speed, and two global behavioural parameters: Aggressiveness and Awareness, defined as distributions, are used to achieve a variation of the desired speeds. Q-PARAMICS also uses the speed limit, defined as fixed value for each road link, but “vehicles will tend to travel using a free-flow speed of approximately 10% higher than the speed limit” (Quadstone Ltd. 2003). The link speed limit can be supplemented by Speed control rules defined for each lane and/or vehicle type. Hence, all three simulators are able to achieve the required heterogeneity of desired speeds, although the approach used by Q-PARAMICS seems less straightforward compared with the other two.

Table 1 Behavioural parameters used in the simulation models

AIMSUN v 4.2	**Q-PARAMICS v4.2**	**VISSIM v 3.70**
Parameters related to **Acceleration**		
Max. acceleration, V, D Max. deceleration, V, D Normal deceleration, V, D	Max. acceleration, V, F[1] Max. deceleration, V, F[1]	Max. acceleration, V, D Desired acceleration, V, D Max. deceleration, V, D Desired deceleration, V, D
Parameters related to **Desired Speed**		
Desired speed, V, D Speed limit, R, F Speed acceptance, V, D	Max. speed, V, F Speed limit, R, F Speed control, R/V, F Aggressiveness, G, D Awareness, G, D	Desired speed, V, D Desired speed Decisions, R/V, D
Parameters related to **Car Following**		
Min. spacing, V, D Reaction time, G, F	Target Headway, G/R, F[2] Reaction time, G, F Aggressiveness, G, D	Desired safety distance, B, F[3] Wiedermann model (8 parameters), B, F[3]
Parameters related to **Gap Acceptance**		
Reaction time, G, F Max. give-way time, V, D Max. GW time var., R, F	Reaction time, G, F Aggressiveness, G, D Patience, G, D	Min. gap time, R, F Dwell time, V, D
Parameters related to **Lane Changing**		
Distance Zone 1, R, F Distance Zone 2, R, F Max. give-way time, V, D Percent overtake, G, F Percent recover, G, F	Signposting, R, F Signrange, R, F Wrong Lane Diversion Time, G, F Awareness, G, D Aggressiveness, G, D	Lane change distance, R, F Emergency stop distance, R, F Min. headway, B, F Max. own deceleration, B, L Accepted own decel., B, L Max. trailing decel., B, L Accepted trailing decel., B, L
Parameters related to **Route Choice**		
Guidance acceptance, V, D Gen.Cost functions, R/V, F	Familiarity, G, F Gen.Cost functions, R, F Cost factor, R, F	Routing Decisions, V, F Gen.Cost functions, V, F

Legend Items in this table are presented with the following syntax:

where <Scope> and	<Value> are one of the following:
G – Global	D – Distribution
V – Vehicle type	F – Fix (constant) value
R – Road link	L – Linear relationship
B – Behaviour type	

Notes:

1. Vehicle Acceleration parameters are defined as distribution in the current version of Q-PARAMICS.
2. Target Headway is a global parameter in Q-PARAMICS, but an adjustment factor can be used in each road link to modify it locally.
3. In VISSIM 2 different car following models can be used, with different parameters. These are part of the Driving Behaviour global parameter set. Several Driving Behaviour sets are defined and each road link in the network can be associated with a different set, thus different behaviour can be modelled in the same network.

The parameters related to *car following behaviour* mainly depend on the car following model implemented in the simulator. AIMSUN uses a variant of Gipps (1981) model, which is based on the following parameters: maximum acceleration and deceleration, normal deceleration, desired speed, minimum spacing between vehicles (when stopped) and the reaction time. The minimum spacing is defined as a distribution for each vehicle type in AIMSUN, and the reaction time is a global, fix parameter, equal to the simulation time step (up to version 4.2 of the model). The Q-PARAMICS car following model is loosely based on a model from Fritzsche (1994), its main parameter is the target headway (in seconds) which determines the spacing of the follower vehicle as a function of its speed. While it is defined as a global constant, it can be modified by a road link-related factor, and it will be different for each DVU depending on the Aggressiveness parameter assigned to the vehicle from a global distribution (Quadstone Ltd. 2004). The reaction time, a global constant parameter, also has a major impact on the car following behaviour in Q-PARAMICS. VISSIM offers a choice of two car following models based on the works of Wiedemann (1974, 1991). These models have several parameters, essentially determining the desired spacing as a function of the speed. While they are all defined as global constants, most without any variation, several Driving Behaviour parameter sets can be defined in VISSIM, and road links in the same network can be assigned to different Driving Behaviour sets.

Gap acceptance is also a highly individual behaviour, but simulators do not provide much opportunity to model the heterogeneity of drivers. AIMSUN defines the reaction time as a fix global parameter. The Maximum give-way time parameter is one which is defined as a distribution for each vehicle type. It is used in AIMSUN to represent the growing impatience of drivers at give-way situations: when a vehicle has been waiting for the Maximum give-way time, it will reduce its safety margins and accept shorter gaps. However, just how short these acceptance gaps are, the AIMSUN manual does not specify, and the user cannot alter the values set in the model. The maximum give-way time variability is a local parameter that can be set for each road link, as an absolute value added to modify the Maximum give-way time for that particular link, so it represents spatial, not behavioural, variability. In Q-PARAMICS, the reaction time is also a global constant, but it is modulated by the Aggressiveness parameter assigned to every DVU, so that drivers with higher aggressiveness will accept shorter gaps. Q-PARAMICS also uses another behavioural parameter, Patience, as a global distribution, to simulate the growing impatience of drivers waiting for a gap at give-way points: if a vehicle has exceeded its patience level, it will just “push its way out into the flow of traffic” (Quadstone Ltd. 2004). The use of this behaviour can be switched on and off by the user, but the values of the Patience parameter are auto-assigned by the model, based on other behavioural parameters such as the Aggressiveness. In VISSIM the user has to define the minimum gap parameter for each give-way and stop conflict point separately, but these are set as constant values, so there is no individual variation in it. The dwell time distribution is used by VISSIM for dwell times at stop signs (also at transit stops), but how exactly this affects gap acceptance behaviour is not clear from the manual.

Lane changing (including merging) is a special, more complex case of gap acceptance behaviour which requires further parameters in the models. However, most model parameters related to lane changing represent spatial and physical characteristics, rather than individual differences. The two Distance Zone limits in AIMSUN define distances from any turning point where the lane changing behaviour of drivers will change, but the change affects all drivers the same way. The Percent Overtake/Recover parameters define the speed differences where drivers would consider overtaking and returning to the slower lane; these are defined as global fix values. The only individual difference is in the Maximum give-way time parameter, which is used in AIMSUN to eliminate potential lane blockages: if a vehicle was unable to complete a lane change during that time, it continues in the wrong lane and becomes a “lost vehicle”. In Q-PARAMICS, the Signposting and Signrange parameters define the maximum/minimum distance range at which drivers become aware of the need that they have to change lane. The actual distance used by each DVU depends on the Awareness parameter assigned to the DVU from the global distribution. The Aggressiveness parameter also affects the gap acceptance behaviour during lane changing. The Wrong Lane

Diversion Time, a global fix parameter, is used in Q-PARAMICS to reroute a vehicle if it was unable to execute a lane change. In VISSIM, the Lane change and Emergency stop distance parameters are used to define the distance limits (from the turning point) within which vehicles attempt to move into the required lane. The Minimum headway (in metres) defines the minimum gap distance at the front and rear of the vehicle required for an acceptable lane change. These are all fixed values assigned to each road link. VISSIM also provides four parameters to define how much deceleration the lane changing vehicle and the trailing vehicle in the target lane are willing to accept. These deceleration parameters are defined by the minimum/maximum values of a linear relationship as a function of the distance from the turning point, based on the assumption that as vehicles get closer to the turning point and the urgency of the manoeuvre increases, drivers are becoming more aggressive and hence use gradually greater deceleration to execute a lane change. While this is a logical and successful concept, the parameters do not represent individual differences among drivers.

Route choice behaviour is primarily affected by the generalised cost functions in all 3 models. The generalised cost functions are related to the road links, although some road links may have different cost functions for different vehicle types, but this is only used for special vehicle categories, e.g. public transport vehicles. In AIMSUN, Guidance acceptance is a vehicle type parameter, defined as a distribution, that affects the use of dynamic rerouting capabilities of vehicles, based on the prevailing, instantaneous traffic conditions. Q-PARAMICS uses the Familiarity parameter, a global fixed percentage, together with a categorisation of the road network into major and minor roads, to model individual route choice behaviour: unfamiliar drivers will only select their route from the major road network, while familiar drivers select from the whole network. A road link-related cost factor can also be used to influence route choice of unfamiliar drivers. VISSIM is significantly different from the other two models in that in its standard form vehicles do not travel between fixed origin-destination points, but they are randomly allocated to user defined routes at routing decision points. VISSIM also has a dynamic assignment option which is similar to the other models, based on generalised cost functions, but this has no parameters related to individual differences.

4 The effects of Desired Speed parameters

One of the most important behavioural parameters is the desired speed, because it has a significant effect on other behavioural characteristics such as car following and lane changing, and it also affects the aggregate traffic flow performance measures, such as flow rate and mean speed. Therefore, a simple hypothetical case study was used to investigate the effects of the available behavioural parameters related to desired speed in the three simulators. A two-lane freeway section with a speed limit of 110 km/h was simulated for a 2-hour period with gradually increasing flow rate, starting at 500 veh/h in the first 15 minutes and moving up to 2,000 veh/h by the last 30 minutes of the simulated period. The flow consisted of 95 % passenger cars and 5% trucks. Several simulation runs were carried out in each simulator with the same input data, and varying values of the behavioural parameters related to desired speed. The results obtained are presented and discussed below.

In AIMSUN the “default” desired speed distributions were used: for cars a distribution with 100 km/h mean and 20 km/h standard deviation, for trucks the mean is 80 km/h and standard deviation is 10 km/h. In the first experiment, the Speed acceptance parameter was set at a fixed value of 1.0 (no variation, default), meaning that all vehicles are fully compliant with the set speed limit, while in the second run a Speed acceptance distribution was used with mean 1.1 and standard deviation of 0.1. Figure 1 shows the speed distributions obtained from the two simulations at various levels of flow rate.

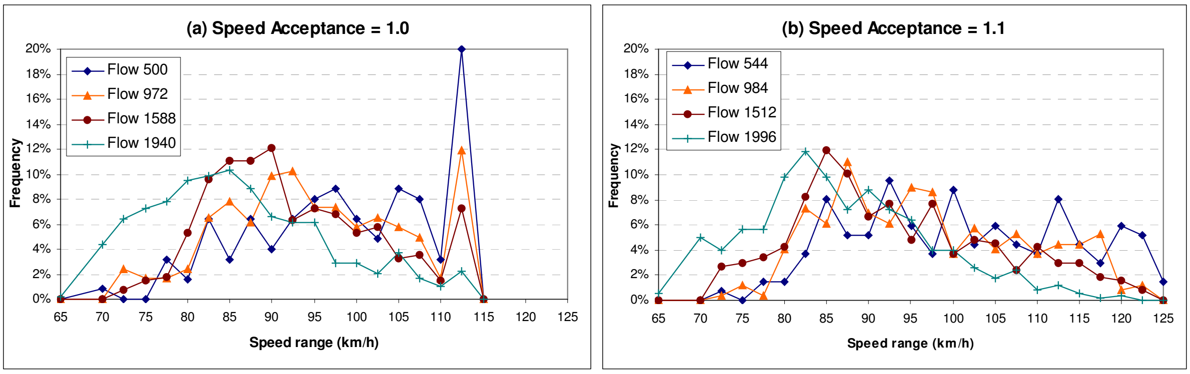

Figure 1 AIMSUN Speed Distributions

Figure 1 (a) shows that the Speed acceptance value of 1.0 effectively cuts down the higher section of the distribution and allocates a speed close to the speed limit to the same proportion of vehicles. When the Speed acceptance is set at 1.1, up to 28 % of the vehicles exceeds the speed limit at low flow rates. As expected, as the flow rate increases, the speed distributions become more constrained by the vehicle interactions and less dependent on the desired speed characteristics, hence the difference between the two experiments decreases. At the starting low flow rate however, there is about 8 to 10 % difference between the two cases in the flow rate and mean speed obtained from the same input data.

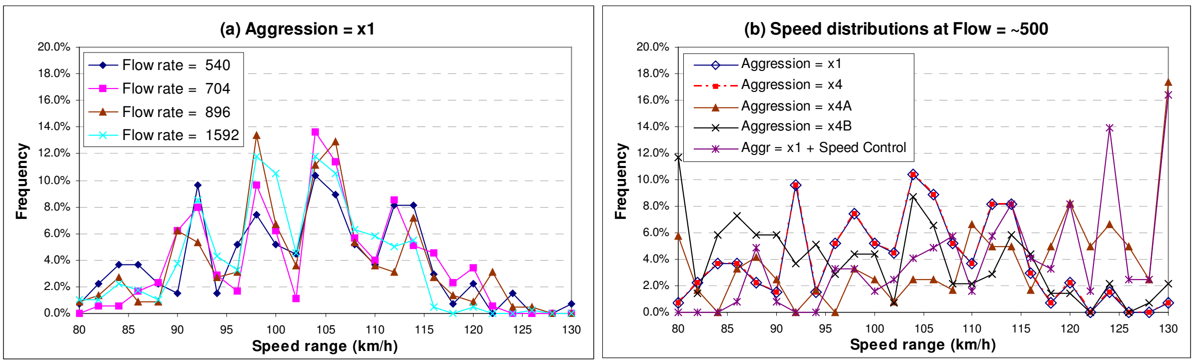

Figure 2 Q-PARAMICS Speed Distributions

In Q-PARAMICS the constant vehicle parameter, maximum speed, is set to 160 km/h, but the desired speed on any link is determined by the link speed limit parameter. In this experiment the link speed limit was set to 95 km/h, because the Q-PARAMICS manual specifies that “Vehicles will tend to travel using a free-flow speed of approximately 10% higher than the speed limit” (Quadstone Ltd. 2003). The distribution of desired speeds is determined by the global Aggressiveness distribution. In the first experiment, the default “x1” normal distribution was used (Figure 2 a). It can be seen that the shape corresponds to a normal distribution, but the dented shape of the curve at any level of flow rate is difficult to explain. About 25 % of the vehicles exceeded the 110 km/h speed limit. Again, the proportion of higher speeds decreases with the increase in the flow rate as the influence of vehicle interactions becomes more dominant. Further experiments were focused on the “free-flow” range of 500 veh/h because it is at this flow rate that most vehicles travel at their desired speed. Different Aggressiveness distributions were set, and the results are shown in Figure 2 (b). The normal distribution with the “x4” values produced exactly the same speed distribution as the original “x1” values, as the “x4” shape represents simply a magnification of the normal distribution. The “x4A” case represents a distribution skewed to the right, and as expected, it produces a much higher percentage of high speed vehicles (61 % as compared with 24 % for the normal distribution cases). The “x4B” case is the opposite, skewed to the left, and the percentage of high speed vehicles dropped to 21 %. An attempt was made to use the Speed Control parameter to create a “hard” speed limit of 110 km/h on the link, but the result was exactly the opposite of what was expected: the proportion of high speed vehicles increased to 66 % with 16 % travelling above 130 km/h. It was later found that the Speed Control parameter overrides the link speed limit parameter, which explains the increase of high speeding vehicles. Overall, it can be concluded that it is difficult to achieve a required speed distribution in Q-PARAMICS, as the effects of the available behavioural parameters are not straightforward.

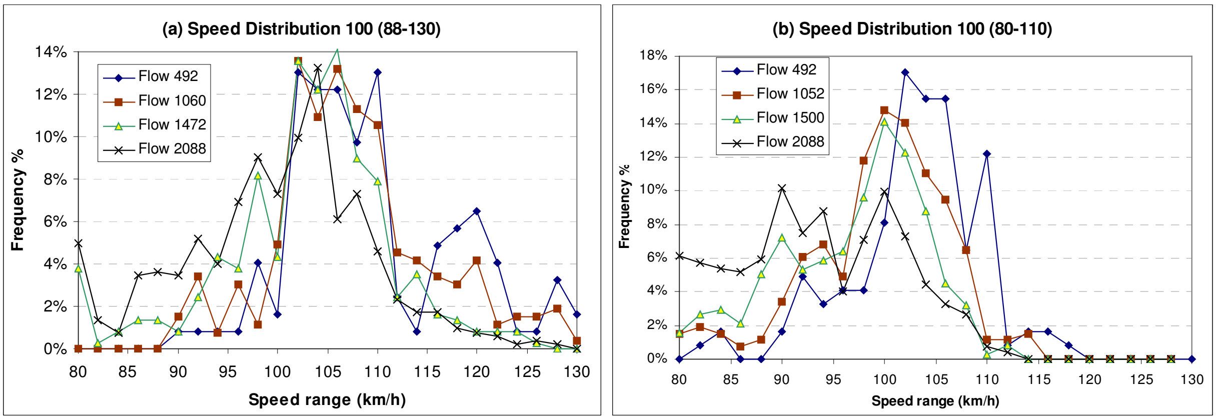

Figure 3 VISSIM Speed Distributions

In VISSIM there is no speed limit as such, the user-defined speed distributions, that can be redefined anywhere in the network at "desired speed decision points", determine the desired speed of the vehicles. These distributions are defined by the user as a cumulative distribution curve between the selected minimum-maximum limits, therefore they can take any shape and form. Figure 3 shows the results of two desired speed distributions, the first one is the default normal distribution between 88-130 km/h limits (Figure 3 a), the second is a skewed distribution attempting to represent a driver population more compliant with the 110 km/h speed limit (Figure 3 b). It can be seen that at the lowest flow rate the resulting speed distributions are closely aligned with the input desired speed distributions, while at higher flow rates the distributions gradually become more dependent on the vehicle interactions.

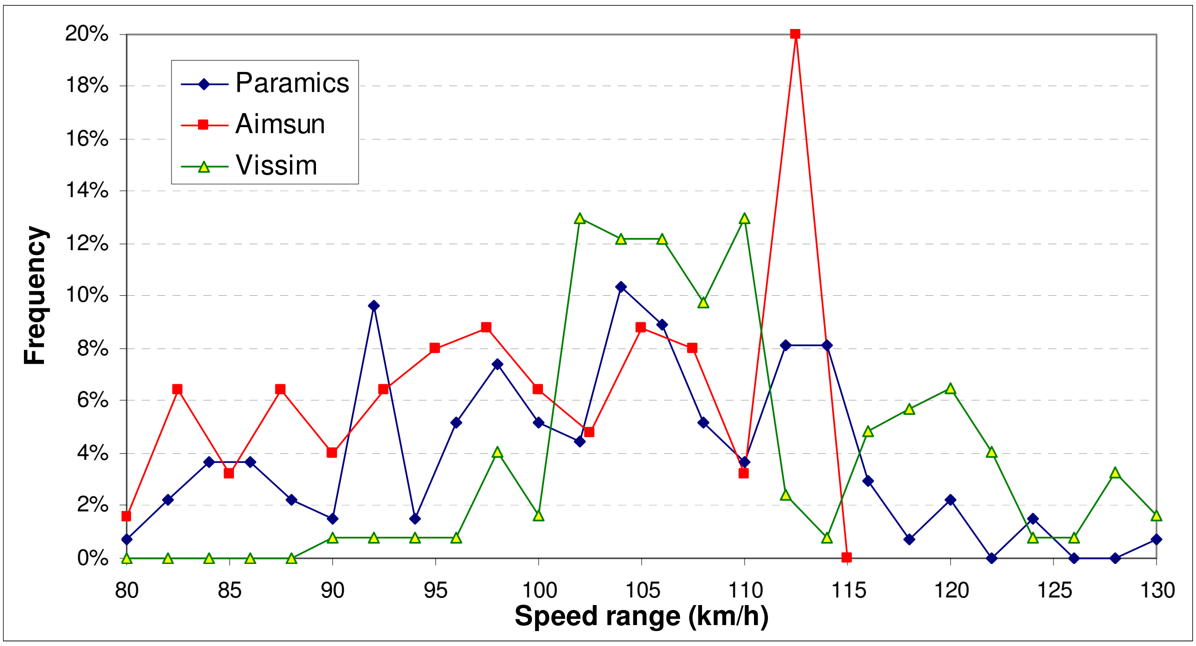

Figure 4 Comparison of Speed Distributions at input flow rate = 500 veh/h

Figure 4 shows a comparison of the speed distributions obtained from the three simulators at the low flow rate representing free flow conditions. These results are based on the "default" desired speed distribution parameters in each simulator, that is, the parameters supplied with the models. It can be seen that while the distributions have a similar shape, there are significant differences between the models, and these also lead to important differences in the aggregate flow performance measures. Table 2 shows the average speed and flow rate values from the three simulators.

Table 2 Comparison of performance measures at input flow rate = 500 veh/h

	AIMSUN v4.2	Q-PARAMICS v4.2	VISSIM v3.70
Mean speed (km/h)	97.6	101.4	108.1
Flow rate (veh/h)	500	540	492

These results demonstrate the differences between the simulators when using the “default” model parameter set. However, it is important to note that there are significant differences between these defaults in the three models, therefore it cannot be expected that the results should be identical. For example, the vehicle type distributions are significantly different in the three models. Also, these experiments were limited to only one simulation run in each model. As these are stochastic models, runs with different random seeds could lead to different results. The variance of the results could be a useful characteristic to investigate, but an average speed distribution from several model runs would blur most of the “individuality” of the results.

The differences in the results also highlight the importance of model calibration and validation for every application. Calibration and validation of a traffic microsimulation model are complex procedures, which typically are limited to the most basic model parameters, such as comparison between observed and modelled link flow and mean speed values. The experiments described above show that other characteristics, such as the desired speed distribution, may also have a significant effect on the model outputs.

5 What do we know about driver behaviour?

The issue presented above leads to the next question: do we know the prevailing values of those behavioural attributes that may be required for model calibration and validation? Unfortunately, in most cases we don’t. It is, of course, not feasible to expect that each model application could include detailed data collection of speed distributions, vehicle acceleration and deceleration observations, just to mention a few required attributes. But if we accept that microsimulation has become an important tool for traffic analysis and evaluation, we should also accept that microsimulation requires a more detailed knowledge of the behavioural characteristics of our vehicle fleet and driver population. Analytical traffic models use mean (and sometimes – rarely –, standard deviation) values to represent average behaviour. Microsimulation models simulate individual drivers and vehicles, therefore they need a distribution of these behavioural attributes to represent realistic behaviour of the modelled population. Research should be conducted to collect data on typical speed and acceleration profiles, on car following and gap acceptance behaviour as used by drivers at various locations and traffic situations to develop guidelines for the users of microsimulation models.

A further problem is the use of such behavioural parameters that cannot be directly measured, eg. aggressiveness, awareness. It is generally accepted that some drivers are more aggressive than others and that this behaviour has an impact on some measurable driving characteristics, but that relationship is not clear and not observable. One might argue that it is not practical to use model parameters that cannot be measured. As aggressiveness is used in Q-PARAMICS to represent individual differences in desired speed, car following, gap acceptance, etc., one might measure some of these observable attributes and use these as surrogate for the aggressiveness distribution. But the limitation of this approach is that while it might seem logical to assume that the distribution of aggressiveness has the same effect on all behavioural characteristics, including desired speeds, car following, gap acceptance etc., no evidence was found to support this assumption. Therefore, an approach using separate distributions for each behavioural characteristic is preferable.

6 Conclusions

Based on the analysis of modelling concepts related to individual driver behaviour Table 3 presents an evaluation of the three models in terms of their abilities to represent the heterogeneity inherent in the traffic flow.

In terms of *acceleration/deceleration behaviour*, VISSIM offers the full range of parameters that the user can define as distributions. AIMSUN uses a similar approach with the exception of desired acceleration. In Q-PARAMICS, acceleration values are defined as a constant for each vehicle type (although this has changed in the current version), and the global distribution of Aggressiveness parameter is used to model the variance of individual differences. This approach is not as straightforward and user friendly as that of the other models. It is also somewhat restrictive because the same distribution affects all vehicle types.

Desired speed behaviour can be realistically modelled in VISSIM using the user defined desired speed distributions at decision points. AIMSUN offers the same level of freedom with the combination of vehicle type related desired speed distribution and speed acceptance. In Q-PARAMICS, different speed distributions can be achieved by the global Aggressiveness and Awareness distributions, but these characteristics are not directly measurable and hence it is more difficult to calibrate for any observed speed distribution.

Table 3 Evaluation of driver behaviour modelling in the simulators

Parameters related to	AIMSUN v4.2	Q-PARAMICS v4.2	VISSIM v3.70
Acceleration	**	*	***
Desired Speed	***	*	***
Car Following	*	**	**
Gap Acceptance	*	*	*
Lane Changing	**	*	**
Route Choice	**	**	*
Legend	* Needs improvement ** Satisfactory *** Excellent		

The parameters related to *car following* are all global and mostly fixed constant values in all three models. The Aggressiveness parameter in Q-PARAMICS is the only exception, however, as a global parameter it is not directly linked to car following behaviour. While the car following models may be able to simulate *average* car following behaviour in a realistic manner, as indeed several studies have proven that they do (eg. see Sakda and Dia 2005), they offer little or no opportunity to represent individual differences in car following behaviour.

Similarly, none of the simulators deals at a satisfactory level with the heterogeneity of drivers in *gap acceptance behaviour*. Again with the exception of the Aggressiveness distribution in Q-PARAMICS, the gap acceptance models use fixed values for reaction time, and while they allow some variation between different sites (like the Max GW time variability parameter in AIMSUN, and the Min. gap time parameter in VISSIM), they consider little or no variability among drivers. The same applies to *lane changing* as a special case of gap acceptance: while VISSIM and AIMSUN have more sophisticated lane changing and merging models, only the Aggressiveness parameter in Q-PARAMICS has an individual behavioural effect on lane changing. Another dimension of driver behaviour is how the waiting time affects gap acceptance during congestion, and AIMSUN is the only simulator that provides a convenient means to model this effect.

In terms of route choice behaviour, AIMSUN and Q-PARAMICS have a behavioural parameter representing drivers' familiarity with the network. VISSIM uses a different approach, which is convenient for small networks where route choice is not an issue, but the dynamic assignment option which is used to model route choice is very tedious and does not deal with individual differences of the drivers.

It is important to reiterate that this evaluation is concerned with the ability of the simulators to represent individual driver behaviour and the critical comments described above should not be interpreted as an assessment of the models' capability of realistically simulating traffic conditions. In fact, all three models were successfully used in a variety of projects. The models are also in continuous development, and some of the identified weaknesses have already been rectified in the latest versions.

Based on this review, it is recommended that models should be improved to deal with individual differences among drivers, especially in modelling car following, gap acceptance, and lane changing behaviour. Parallel with the suggested model improvements, it is also necessary to conduct research to collect information on the existing range of behavioural attributes of the driver population in different locations (eg. motorways, rural highways, urban arterials) and under different flow conditions at various levels of congestion.

It may be argued that there is no need to model such a wide range of individual behavioural differences in microsimulation models as long as the aggregate performance measures that most users wish to obtain are within an acceptable level of accuracy. While it may be true that simulators are typically able to achieve the required accuracy, it is also well known that more problems are reported when modelling difficult traffic scenarios especially in congested conditions. It is suspected that part of these problems may be caused by the weaknesses in modelling individual differences among drivers: for example, if all drivers have the same car following behaviour, then there will be little variation in the headways and gaps between the vehicles and this, in turn, will make lane changing far more difficult. Therefore, one way of reducing the occurrence of such problems may be to develop more detailed models of individual driver behaviour.

7 Acknowledgements

The author is grateful to Prof Jaime Barcelo (TSS) for providing access to the AIMSUN NG simulator for research purposes, to Martin Fellendorf (PTV AG) for providing a copy of the VISSIM simulator for research purposes, and to Hussein Dia at the University of Queensland for providing access to Q-PARAMICS through the ITS Laboratory project in which UNSW is a partner.

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