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Modelling safety-related driving behaviour—impact of parameter values

Peter Bonsall [a], Ronghui Liu [a,*], William Young [b]

[a] *Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, UK*
[b] *Department of Civil Engineering, Monash University, Australia*

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Abstract

Traffic simulation models make assumptions about the safety-related behaviour of drivers. These assumptions may or may not replicate the real behaviour of those drivers who adopt seemingly unsafe behaviour, for example running red lights at signalised intersections or too closely following the vehicles in front. Such behaviour results in the performance of the system that we observe but will often result in conflicts and very occasionally in accidents. The question is whether these models should reflect safe behaviour or actual behaviour. Good design should seek to enhance safety, but is the safety of a design necessarily enhanced by making unrealistically optimistic assumptions about the safety of drivers' behaviour?

This paper explores the questions associated with the choice of values for safety-related parameters in simulation models. The paper identifies the key parameters of traffic simulation models and notes that several of them have been derived from theory or informed guesswork rather than observation of real behaviour and that, even where they are based on observations, these may have been conducted in circumstances quite different to those which now apply. Tests with the micro-simulation model DRACULA demonstrate the sensitivity of model predictions—and perhaps policy decisions—to the value of some of the key parameters. It is concluded that, in general, it is better to use values that are realistic-but-unsafe than values that are safe-but-unrealistic. Although the use of realistic-but-unsafe parameter values could result in the adoption of unsafe designs, this problem can be overcome by paying attention to the safety aspects of designs.

* Corresponding author. Tel.: +44 113 3435338; fax: +44 113 3435334.
E-mail address: rliu@leeds.ac.uk (R. Liu).

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The possibility of using traffic simulation models to produce estimates of accident potential and the difficulties involved in doing so are discussed.

1. Background

It is widely recognised that vehicles are sometimes, perhaps often, driven unsafely. Some drivers are ignorant of such fundamentals as safe stopping distances and others willfully ignore them—usually in order to get to their destination more quickly. Should models seek to replicate such behaviour? On the one hand it might be held that models should be as accurate as possible and that if unsafe behaviour occurs in real life it would be wrong to pretend otherwise. On the other hand, it could be thought unethical to design a scheme using a tool which assumes unsafe behaviour if this could lead to the adoption of designs which are known to be unsafe. *Is it "right" in a detailed traffic simulation model to use parameter values which represent the actual behaviour of drivers even though this behaviour might be unsafe*, *or would the use of unsafe parameters contribute to the adoption of unsafe designs?* and, to the extent that the answer to this question is ambiguous, *should ethical issues impinge on the selection of parameter values?*

These were the questions which seem incapable of quick resolution and intriguing in their ramifications, and which therefore stimulated us to write this paper. We agreed that, in exploring the issue, we should question where the parameters in well known traffic micro-simulation models have come from and whether they represent real behaviour or some idealised safe behaviour. We should investigate the sensitivity of model predictions to the value of key safety-related parameters and should discuss the whole question of the representation of unsafe situations in traffic micro-simulation models. Having done this, we should consider the consequences of using safe-but-unrealistic and realistic-but-unsafe parameters and then attempt to come to a conclusion on the question of the ethical, and potentially legal, issues involved in the choice of model parameter values. This paper attempts to follow that agenda.

2. Safety-related parameters in traffic simulation models

The progress of individual vehicles in a detailed traffic simulation model is the result of applying rules and formulae to determine aspects such as:

- speeds in free-flowing traffic;
- headways between vehicles;
- acceleration and deceleration profiles;
- interaction between priority and non-priority vehicles;
- overtaking and lane-changing behaviour; and
- adherence to traffic regulations—notably compliance with traffic signals and adherence to speed limits but also to regulations on the use of bus lanes, one-way streets, banned-turns, etc.

All of which are obviously related to safety. In fact, as Young et al. (1989) point out, most of the parameters used in micro-simulation models have implications for safety—even a parameter as seemingly neutral as the simulation interval will have an impact on safety if, as is commonly the case, it effectively defines the drivers' reaction time.

Most of the behaviours listed above are determined in traffic simulation models via sub-models representing car-following, gap-acceptance and lane-changing behaviour. These models are, in turn, dependent on parameters which are deemed to encapsulate the relevant aspects of driver behaviour. These models, the associated parameters and the values typically adopted for them are described in the following sub-sections and summarised in Table 1.

2.1. Car-following models

Car-following models represent the longitudinal interaction among vehicles in a single stream of traffic. The speed of the following vehicle is assumed to respond to stimulus from the vehicle or vehicles in front. The stimulus is usually represented in terms of distance and speed differences. One of the widely used car following model is that proposed by Gipps (1981) which combines a free-flow driving model with a stopping-distance based car-following behaviour model. This model, or variations on it, has been implemented in micro-simulation software packages such as AIMSUN (Barcelo et al., 1995), SISTM (Wilson, 2001), and DRACULA (Liu, 2003).

Some authors reserve the term 'car-following' exclusively for the preceding/following situation while others extend it to cover anything related to the longitudinal progress of vehicles (thus including the determination of free-flow speeds, acceleration and deceleration profiles and response to traffic signals). We need not concern ourselves here with such distinctions, nor with the variety of forms that the car-following models can take; our immediate concern is solely with the parameters required to determine the longitudinal progress of vehicles.

Taking the broadest definition of the car-following model, the main parameters used in the models are:

2.1.1. Desired speed

Desired speeds of the drivers are generally modelled as input parameters and are often directly made equal to the free-flow speeds on the link or road. The later may vary according to the character of the road. For example, a dual-carriage road and a wider road may lead to higher free-flow speeds than residential streets. City-centre streets where there are lots of pedestrians and pedestrian crossings will force the free-flow speeds down, as would excessive curvature or gradient. Speed limits are used as a proxy for free-flow speeds—a practice with interesting implications to which we will return in a later section of the paper.

2.1.2. Desired headway

Car following algorithms generally assume a minimum safe headway which a following vehicle wishes to keep. This may be represented as either a time or a distance headway. When the following and the lead vehicle driver are at the same speed, the time headway represents the time available to the driver of the following vehicle to reach the same level of deceleration as the lead vehicle in case it brakes. This available time is independent of speed. The Gipps model uses a 1–2 s time headway.

Table 1
Safety-related parameters commonly included in traffic simulation models

Parameter	Type[a]	Notes	Typical values[b]	Source
Desired speed	Behavioural and policy	Generally link-specific, should reflect the speed limit, the road layout and frontage and the amount of pedestrian activity	Legal speed limit	Assumption
			Speed of vehicles that have headways >6 s	Vogel (2002), inferred from observation
Desired headway	Behavioural	May be expressed in units of time or distance	2.2 s	May (1965), observation
			1.5–2.5 s	Vogel (2002), observation
			2.12 s (with s.d. of 0.86)	Michael et al. (2000), observation
			2.19/5.96 s for car/truck	Robertson and Abu-Lebdeh (2001), observation
			6.5 m	Gipps' (1981), guesswork
Reaction time (s)	Physiological	May not be explicitly represented (may be inherent in the simulation interval)	1.5	May (1990), General Motors test track
			1.2–1.4	Forbes et al. (1958), observation in tunnels
			0.67	Gipps (1986), theoretical estimate
			0.75–3.0	TRB (1999), observation
			0.75–1.71	Johnsson and Rumer (1971), observation

			0.85–1.6 for young drivers	Olson et al. (1984), observation
			0.57–1.37 for older drivers	Olson et al. (1984), observation
			1.5–3.0	Neuman (1989), observation
			2.74	McGee (1989), observation
Rate of acceleration (m/s^2)	Behavioural (constrained by vehicle performance)	May distinguish between normal rate of acceleration and maximum rate of acceleration, may differ depending on vehicle type	For cars:	
			1.5–3.6 max acceleration	ITE (1982), observations?
			0.9–1.5 normal acceleration	Gipps (1981), theoretical estimate
			For buses: 1.2–1.6	Firstbus (private communication)
Rate of deceleration (m/s^2)	Behavioural (constrained by vehicle performance)	My distinguish between normal deceleration and emergency braking, may differ by vehicle type	1.5–2.4 emergency	ITE (1982), observations?
			0.9–1.5 normal	ITE (1982), observations?
			3.0	Gipps (1981), theoretical estimate
Critical gap (s)	Behavioural	From the back of one vehicle in the target stream to the front of the following vehicle in that stream	3.5	Gipps (1981), theoretical estimate
			4.75	Kimber et al. (1986), observations
			4–8.5	TRB (1985), design data

Stimulus required to induce use of the reduced gap (s)	Behavioural	Time spent waiting for acceptable gap number of rejected gaps	120	Mahmassani and Sheffi (1981), guesswork
Minimum gap (s)	Behavioural		1.0	Guesswork
Willingness to create gaps to assist other vehicles to change lanes	Behavioural	May be expressed as the percentage of the priority traffic stream who stop accelerating or even start decelerating once they "see" there is minor flow traffic waiting to merge or cross. May vary depending on what type of the other vehicles are.	20% for other cars 70% for buses	Guesswork
Rules for mandatory lane change	Behavioural and policy	May simply reflect traffic regulations but may vary depending on enforcement policy	Published regulations	n.a.
How far ahead the drivers anticipate the need to change lanes	Behavioural and policy	The behavioural element may be constrained by sight lines, etc.	1 to 2 links, or 500 m	Liu (2003), Nsour and Santiago (1994), guesswork
Minimum acceptable gap when changing lanes	Behavioural	As in gap-acceptance model	As in gap-acceptance model	As in gap-acceptance model
Variation in the gap depending on the urgency of the desire to change lanes	Behavioural	May depend on size of time advantage or distance remaining before mandatory change must be completed	50–100 m or 5–10 s	Guesswork

Willingness to create gaps to assist other vehicles to change lanes	Behavioural	May be expressed as the percentage of the traffic in the target lane who stop accelerating/start decelerating once they "see" a vehicle attempting to enter the lane	20% for other cars 70% for buses	Guesswork
Level of compliance	Behavioural and policy	May differ for different types of regulation Should vary depending on enforcement policy	50–100%	Some observations e.g. Gipps (1986) for lane changing, and Liu and Tate (2004) for speed compliance
Distribution of aggressiveness	Behavioural	Sometimes used to control the proportion of drivers in each of several preset categories, each category being characterised by different values for each of the aggression-related parameters described above. Used to make model predictions fit observed indicators of the operational performance of the system (e.g. speed, throughput)	n.a.	n.a.

[a] Note that, when modelling the performance of advanced driver-assistance devices or of a full automated highway system, several of these parameters would become functions of the system specification and thus, effectively, they become policy variables. For example, in work to test the impact of in-vehicle speed control devices on the operational performance of a network, Liu and Tate (2000) modified parameters in DRACULA to make speed limit compliance vary as a function of the assumed penetration of speed control devices in the vehicle fleet.

[b] Note that most models use a distribution of values in preference to a single value.

2.1.3. Reaction time

Reaction time is a key dimension in both car-following and lane-changing models. It represents the driver's ability to react to situations and make particularly decisions. Gipps used a 2/3 s reaction time for all drivers, whilst DRACULA samples from a range between 0.8–2.0 s for individual drivers.

2.1.4. Normal and maximum acceleration

Drivers may apply a smaller acceleration in a more relaxed following situation, whilst they may apply the full acceleration power of their engine when trying to overtake or pass through a green light. A normal acceleration rate of 1.2 m/s^2, and a maximum acceleration of 1.6 m/s^2 for cars has been assumed by Gipps.

2.1.5. Normal and maximum deceleration

Drivers may apply a gentler deceleration when approaching a known obstacle or an obstacle visible a long way upstream, such as approaching a traffic light or a slower moving vehicle in front. A harsher deceleration may be applied for emergency breaking, such as in response to a sudden deceleration of the vehicle in front or to a sudden lane-changing from adjacent traffic. A normal deceleration of 2.5 m/s^2 and maximum deceleration of 5.0 m/s^2 are the default values adopted in DRACULA.

2.2. Gap-acceptance models

Gap-acceptance models deal with process by which a driver finds an acceptable gap in a traffic stream when (s)he wants to cross or merge into that stream. They are fundamental in representing conflicts between high and low priority flows and in determining how a vehicle from a low priority flow will cross or merge into a higher priority flow. The models are used to deal with aspects such as overtaking which involves use of the opposing carriageway (*how much of a gap in the opposing flow is required?*), lane-changing (*how much of a gap or gaps in the traffic using the intended lane?*), and uncontrolled pedestrian movements (*how much of a gap in the traffic flow will a pedestrian require before attempting to cross a carriageway?*).

Gaps are usually represented in time (s). The key parameters for gap-acceptance models include:

2.2.1. Critical gap

A driver or pedestrian will accept a gap in the traffic stream to contemplate his intended manoeuvre if the gap is longer than the critical gap (Hewitt, 1983). The critical gap will clearly differ between drivers and it is therefore modelled in DRACULA and some other models as a random variable drawn from an assumed probability density distribution of critical gaps in the population.

2.2.2. Gap-reduction and minimum gap

Some gap-acceptance models use a fixed value for each driver, others allow critical gaps to be situation-dependent in order o reflect the phenomenon of impatient drivers for whom the critical gap decreases with each passing gap (Kimber, 1989). This gap-reduction behaviour can be recognised by observing drivers who reject a gap which is longer than the one eventually accepted. The stimulus required to induce the decrease of critical gap has been modelled as the number of passing gaps (e.g. Mahmassani and Sheffi, 1981) and, in DRACULA, as the time spent in searching for acceptable gap. Clearly, the critical gap can not decrease infinitely, hence a minimum gap is often used in the models to set a lower boundary to the formulation.

2.2.3. A ''gap-creation'' situation

Some gap-acceptance models allow for the fact that drivers in the priority flow may take pity on drivers waiting for a gap and may deliberately slow down in order to create a gap. This is represented in DRACULA via a parameter to indicate the percentage of traffic having a *willingness to create gaps*.

2.3. Lane-changing models

Lane-changing models consider the individual driver's intention and ability to change lanes. An *intention* to change lanes will reflect the advantage to be gained (e.g. an increase in speed or an avoidance of delay) or the need to do so (e.g. in order to comply with a traffic regulation, to avoid an incident in the current lane, or to prepare for a turning movement). The intention to make a lane-change may be triggered when the time advantage to be gained by changing lanes exceeds some *critical value*. Some models may allow drivers to anticipate the need for a change of lane, in which case a parameter will be required to determine *how far ahead the drivers anticipate*.

The *ability* to change lanes will be a function of the lane space available and the relative speeds and locations of surrounding vehicles and is generally modelled in a way which is analogous to a gap-acceptance model. The parameters controlling this model will thus include the *minimum acceptable gap* in the target lane, together, perhaps, with parameters which allow for *variation in the gap depending on the urgency of the desire to change lanes* (see Taylor et al., 2000), and the *willingness to create gaps* by kind-hearted drivers in the target lane.

The driver's intention to change lanes is a complex decision-making behaviour, involving answer questions such as: *is it possible to change lane? Is it necessary to change lane? and is it desirable to change?* The lane-changing models need first of all to identify the reasons for such intention. The following are a list of but few: bus stopping at bus stops; avoiding an incident (parked vehicle, road works, accidents); making junction turning movements; and overtaking a slower moving vehicle.

Perhaps the most complicated part of a lane-changing model is its formulation of a driver's lane-changing intention as decision-making tree. It appears that there is no universally accepted structure for this process; each model or package has a unique list of lane-changing reasons a unique structure for the decision-making process.

Once a lane-changing intention is triggered, a gap-acceptance model is used to find the gaps in the target lane which are acceptable to the driver wishing to change lanes. The parameters considered here are front gap and rear gap (lag) in the traffic stream of the target lane, and the critical gap acceptable to the driver. The parameters in the gap-acceptance models for lane-changing situation are similar to those in the general gap-acceptance models described above.

2.4. Adherence to regulations

This factor is rarely introduced into models. Adherence to traffic regulations may be modelled using assumed *levels of compliance*—these may differ for different types of regulation and should, ideally be treated as policy variables reflecting different levels of enforcement.

2.5. Representations of parameter values

Most models use a distribution of values, rather than a single value, for their key behavioural parameters. It should also be noted that, although some models use the same parameter value, or distribution of values, for all vehicles and drivers, others allow different values or distributions for different classes of vehicle and for different 'types' of driver. For example, the PARAMICS (Laird et al., 1999) and CORSIM (Rathi and Santiago, 1990) models recognise various categories of driver according to the '*aggressiveness*' of their driving style (the more aggressive drivers accept smaller gaps, accelerate and decelerate more rapidly, and so forth). The proportion of people in each preset 'aggressiveness' category is not based on any real data but is a variable which can be adjusted as part of the process of getting the simulation model to reproduce aggregate statistics such as average speeds or flow throughput. The process of model fitting is of course crucial to the use of the model but, as we will see later in this paper, it can be argued that problems are likely to occur if this is done simply by adjusting the proportion of drivers in each of the preset aggressiveness categories. The DRACULA model (Liu et al., 1995) allows the user to specify the distribution of values for each parameter—an approach which overcomes the problem of using preset aggressiveness categories but which obviously requires more data.

2.6. Summary of data sources

Table 1 lists the parameters identified above, indicating commonly adopted values and the sources of these values. The second column of the table distinguishes between purely behavioural parameters, those which represent behaviour which is constrained by vehicle performance, those which reflect policy and those (of which reaction time is the only example) which are in some sense fundamental. It can be argued that each of these types of parameter has a different role in the model and that different rules should apply in selecting values for them.

The fourth column of Table 1 presents typical values for the parameters but it is clear that, for some parameters, quite different values are adopted in different models—although it should be noted that, due to differences in the models, not all the values are strictly comparable.

It is apparent from the fifth column of Table 1 that the values of several of the key parameters are based on speculation or theory rather than on actual observations. Even those which are based on observations are often reliant on data for a limited range of vehicle types and, in some cases, on data collected decades ago in particular driving conditions and their applicability to 21st century driving conditions, sometimes on different continents, may be questioned.

3. The impact of unsafe driving on system performance

3.1. Acceptance of risk—how drivers really drive

Before examining the implications for model predictions it is worth considering the impacts that unsafe driving has for system performance. Section 2 has listed a number of key parameters in simulation models. This section explores some of them in a little more detail and, introduces the concept of risk. Risk represents the probability of an accident occurring. Drivers accept risk when they drive a car and behave in the light of their own perception of the size of the risk and of their attitude to it.

It is not difficult to think of situations in which a proportion of drivers, perhaps the majority, drive in a way that is not commensurate with maximum safety. These obviously include:

- adoption of inadequate headways in fast moving traffic (below the calculated 'safe stopping distance'),
- speeding (in excess of the legal limit or in spite of local circumstances),
- excessive reliance on the vehicle's brakes (even in adverse weather conditions),
- nearside overtaking (where illegal and therefore unexpected by other drivers),
- reckless overtaking (e.g. where sight-lines are inadequate),
- passing traffic signals at orange (or even red).

We will consider some of these in a little more detail and, in doing so, will recall that most drivers have no precise idea of how safe or dangerous a manoeuvre might be but that they make assumptions based on assumptions about their reaction times and those of other drivers, and about the performance of their vehicles. A driver's reaction time is a key determinant of the degree of safety with which he can complete a given manoeuvre or maintain a given headway. In reality, many drivers overestimate the speed of their reactions and, by driving accordingly, they are contributing to a marginal increase in system performance but also to the likelihood of an incident which, were it to occur, would have severe consequences for system performance as well as for life and limb.

3.1.1. Safe headways

Simplifying somewhat, the reaction time assumed by UK highway designers in the determination of stopping sight distance is 2 s (DOT, 1993). If all the vehicles were travelling at the same speed then a vehicle that immediately stops would require the following vehicle to be travelling at a headway of 2 s. This separation headway would result in traffic flows of 1800 vehicles per lane per hour. However, research has shown that freeway traffic moves at much lower headways and thereby achieves much higher flows per lane.

Research by Oates (1999) suggested that almost 50% of drivers on congested stretches of the M62 motorway were driving with headways at or below 2 s and that almost 25% were driving with headways at or below 1 s. This clearly indicates that drivers are driving unsafely. Simple calculation indicates that, in smooth conditions and constant speed, the flow achievable with a 0.5 s headway would be about four times that achievable with a 2 s headway. However, the adoption of 0.5 s headways would clearly assume unsafe behaviour since no vehicle could stop if the vehicle in front suddenly stopped at this speed, hence causing incidents. Given that incidents are likely to be more frequent at low headways and that, until the debris is removed and the shockwaves have dissipated, incidents have a dramatic effect on network performance. Maximum network performance is probably achieved at average headways of around 1.5 s.

3.1.2. Gap acceptance

A driver's gap-acceptance behaviour is a function of his or her perception of risk and reward. This perception can change—for example acceptance of risk tends to increase if a driver has already been waiting a long time (Taylor et al., 2000). In real life, the choice of short gaps will sometimes, all be it rarely, result in an accident and consequential delay to traffic but more usually it will help to keep the network moving.

3.1.3. Stopping at red lights

Traffic signals are used as safety devices and to manage the flow of traffic by temporal separation of conflicting movements. The rule is that drivers should stop at traffic signals when the lights are red. In practice, of course, many drivers do go through red lights and this is pragmatically recognised by the inclusion of all-red phases even though incorporation of dead time reduces the performance of the system. In fact the potential deterioration in performance is marginally reduced because some drivers do disobey the rules; Pretty (1974) found that traffic signals improved capacity at an intersection previously under police control only because drivers used the amber and all-red periods.

3.1.4. Adherence to speed limits

Roads are generally designed for a speed which is exceeded by no more than 15% of the traffic. In his development of relationships between speeds and the geometric characteristics of rural roads, McLean (1978) concluded that about 15% of drivers were likely to exceed the speed limit and that optimal design should recognise this fact. It is commonly observed that free-flow speeds are often well in excess of the speed limit and that, in the absence of congestion, such speeds appear to be able to be maintained almost indefinitely.

3.2. The impacts of unsafe driving on network performance—in reality and in models

Similar arguments can be made in respect of each of the unsafe-driving cases mentioned earlier. Unsafe driving will generally lead to enhanced system performance but when, as is inevitable, there is an incident, the results can be catastrophic not only for life, limb and property, but also in terms of disruption to the smooth flow of traffic. On balance, however, provided that incidents remain relatively rare events, it is reasonable to conclude that *if everyone were to drive in strict accord with guidelines and regulations, the effective capacity of the network would be reduced below the levels currently observed.*

However, most simulation models do not allow accidents to occur and so ignore the question of risk and of the consequences that an accident might have for network performance. By ignoring the possibility of these rare events, traffic simulation models are representing only one side of the safety/efficiency equation; the half that sees only benefit from drivers' acceptance of higher risks.

They have no mechanism for reflecting the advantage of safety measures such as stricter enforcement of speed limits or the incorporation of all-red phases at traffic lights.

If a simulation model were to assume that all drivers adopted headways which were safe, this would, given a realistic distribution of reaction times, require the assumption of longer headways than are observed in practice and this would result in an underestimate of achievable traffic flows and hence in incorrect estimates of the performance of the traffic system. Similarly, if traffic simulation models were to allow that not all drivers stop at red lights this would result in an underestimate of the achievable traffic flow.

As noted in a previous section, simulation models commonly assume that drivers' desired speed is the free-flow speed and that this may be proxied by the speed limit. This assumption not only raises the curious concept of a limit which no one wishes to exceed (in which case why is it needed?) but, more seriously in the current context, implies that all vehicles will travel at or below the speed limit irrespective of the lightness of the flow. This assumption must result in an underestimate of the performance of the traffic system.

4. Simulation tests

In order to illustrate the general argument made above, the DRACULA model was used to explore the impact that changes in key behavioural parameters might have on various model estimates of system performance. The results reported here relate primarily to the total travel time in the test network since this is the indicator of system performance most widely used to inform investment decisions.

The first test was designed to show the effect of unrealistically assuming full compliance with speed limits. The test was based on an urban network in east Leeds covering an area of 3 km by 10 km. The results, shown in Table 2, relate only to traffic on the roads subject to a 30 mph (≈50 kph) speed limit.

It is clear that, if we assume full compliance with the speed limit, the total travel time in the network would increase. Given that the observed level of compliance is lower in the off-peak period, one might have expected that the effect of assuming 100% compliance would be more marked in the off-peak. In fact this is not the case. The off-peak effect seems to be reduced because of a

Table 2
Predictions of the effect of different levels of speed limit compliance

	Total travel time (veh h) in the network	Travel time (veh h) at speeds below 10 kph
Peak hour flow (18,000 vph)		
Normal compliance (80%)	1093	538
Assumed full compliance (100%)	1155	569
Difference	(+5.6%)	(+5.7%)
Off peak hour flow (12,000 vph)		
Normal compliance (66%)	440	66
Assumed full compliance (100%)	453	50
Difference (%)	(+2.9%)	(−24.2%)

marked reduction in congestion (as indicated by total travel times at speed below 10 kph) during this period. We speculate that this is because, in the absence of the fast vehicles, there is less to interfere with the smooth flow of traffic during low flow conditions than there is during the peak (Liu and Tate, 2004).

The results of this test demonstrate how a change in the assumed compliance with speed limits can affect the overall performance of the system and that this effect differs according to the time of day in ways which might not have been predicted in advance.

The second set of tests was designed to show how assumptions about the distribution of one aspect of aggressive driving (in this case the normal and maximum rates of acceleration and deceleration) can affect the predicted performance of a scheme. The tests relate to the introduction of partial signalisation at a roundabout just off the M25 near Heathrow Terminal 5. The mean values of the acceleration/deceleration distributions used in the tests are shown in Table 3 (note that traffic at the site is 10% HGV and 90% car). The tests relate to two flow level scenarios; a current flow and a future flow at twice the current level—as can be expected when the new Terminal opens.

The results of the tests are shown in Table 4. As might be expected, the effect of the signalisation scheme is very dependent on the assumed level of flow; at current flow levels the signalisation would lead to an increase in journey times whereas, at future high levels, it would lead to a very marked reduction in journey times. More interestingly, in the light of the theme of the current paper, it is clear that the assumed level of acceleration/deceleration affects the predicted impact

Table 3
Mean acceleration and deceleration rates used in the roundabout signalisation tests

	Default acceleration and deceleration		More aggressive acceleration and deceleration	
	Car	HGV	Car	HGV
Normal acceleration (m/s^2)	1.5	1.2	2.5	2
Max acceleration (m/s^2)	2	1.6	2.5	2
Normal deceleration (m/s^2)	2	1.5	2.5	2
Max deceleration (m/s^2)	5	2.5	5	3.5

Table 4
DRACULA predictions of the effect of roundabout signalisation, measured in vehicle hours in the local network

	Priority roundabout	Partially signalised roundabout	Difference (%)
Current flow scenario			
Modest acceleration/deceleration	50.0	52.6	+5
Aggressive acceleration/deceleration	46.4	51.4	+11
Aggressive acceleration/deceleration	(−7%)	(−2%)	
Future high flow scenario			
Modest acceleration/deceleration	227.5	81.8	−64%
Aggressive acceleration/deceleration	171.2	70.1	−59%
Difference	(−25%)	(−14%)	

of the signalisation scheme. If a more aggressive level of acceleration/deceleration is assumed, journey times are much reduced—particularly while the roundabout is operating under normal priorities and under the high flow scenario.

The net result is that the assumption of more aggressive acceleration/deceleration causes a doubling of the dis-benefit associated with signalisation under current flow conditions but causes a reduction in the large benefit predicted under high flow conditions. It is clear that the assumptions about levels of acceleration and deceleration can profoundly affect the prediction of scheme benefits and that this effect differs according to the flow level.

5. Discussion

5.1. Implications of choice of parameter values on safety

The previous sections have highlighted some of the key safety-related parameters in simulation models and provided examples to illustrate the choice of parameter values on system performance. Clearly, the value of the parameters will affect the model predictions, but what are the implications of this for design, for investment decisions, and for the behaviour of travellers? We will consider this question separately for the different types of parameter identified in Table 1.

Errors in *parameters reflecting fundamentals of human physiology or of the performance of vehicles or system components* could have serious implications for the design of system components such as sight lines or inter-greens. For example; an overoptimistic assumption about drivers' reaction times or vehicles' braking performance will lead to overestimation of the operational performance (defined in terms of flows and journey times) and of the safety of the system. Pessimistic assumptions will lead to similar underestimations. Although both might lead to sub-optimal investment decisions, it can be argued that the results of an overestimation of the operational performance and safety of a system are potentially more severe than those of an underestimation. Overestimation of operational performance or safety may lead to the adoption of unsafe or inefficient designs, underestimation of performance or safety may lead to over specification of the design and, as a consequence of this, perhaps to fewer schemes being built. It seems reasonable to conclude that the analyst should therefore err on the side of underestimating the capabilities of drivers, their vehicles and other system components.

For *parameters reflecting policy or behaviour* the situation is much more complex because the consequences of using the wrong parameter value will depend on the way that the model is being used. This complexity results from the fact that a given error in the parameter value will affect the predictions of operational performance in the opposite direction. For example, if the assumed adherence to speed limits is too low the model will over estimate the operational performance of the system whereas if the assumed adherence to speed limits is too high the model will underestimate the operational performance of the system. As will be seen, the consequences of this will be quite different depending on the way the model is being used.

We begin by considering the situation where the model is being used to identify schemes which meet predefined operational performance criteria. The use of safe-but-unrealistic parameter values in such circumstances will result in the rejection of schemes which would have met the criteria had more realistic values been used. This in turn would tend to lead to the adoption of schemes whose capacities, and costs, are greater than necessary. Not only would this represent misuse of resources but the oversupply of capacity might lead to the induction of additional traffic. The use of realistic-but-unsafe parameter values would produce no such problems. However, if the candidate schemes are not subject to safety audit and if no estimate of the safety of each scheme is being produced by the model, it is clearly possible that unsafe designs would be adopted—we return to the question of how traffic simulation models might produce indicators of safety in a later section of this paper.

We now consider the situation where the model is being used as part of an evaluation of alternative schemes, including the do minimum, in order to identify the one which represents the best value for money. The process will, by definition, include an assessment of the safety consequences of each scheme as well as of its operational performance (although, in the absence of safety indicators from the traffic simulation model, the safety aspects may not be dealt with consistently—again, we will return to this issue in a later section of this paper). There will be a general tendency for unrealistically 'safe' parameter values to result in an underestimate of the operational performance of the scheme but to provide an over estimate of its safety. The use of unrealistically unsafe parameter values will similarly tend to result in over estimation of the operational performance of the scheme but underestimation of its safety. Either case would lead to incorrect assessment of scheme worth and it would clearly be better to use realistic values for all parameters.

It should be noted, in passing, that, in order to avoid bias in the appraisal process, all parameter values should be equally realistic. For example if the parameter value for, adherence to traffic signals, were more unrealistically 'safe' than any other parameter value, the model would underestimate the operational performance of (and overestimate the safety of) a scheme which involved a major programme of signalisation. Conversely, an overly safe assumption about gap acceptance would deflate the safety improvement (and inflate the operational improvement) to be expected from signalisation of a priority intersection. The consequences of these errors would depend on the relative weights given to the operational and safety aspects in the appraisal, but it would certainly bias the outcome. The use of realistic-but-unsafe parameter values would not distort the appraisal process provided that full account is being taken of the safety indications of each design.

If proper account is *not* being taken of safety indications it is possible that the use of realistic-but-unsafe parameter values could promote the adoption of unsafe design elements. For example, a model which allows unsafe overtaking would reflect the operational advantage to be gained by this activity and would therefore tend to favour schemes which give most opportunity for it to occur. Other things being equal, a scheme with a single carriageway comprising two lanes will therefore operationally outperform one with a dual carriageway comprising one lane in each direction. The implication is that, by allowing the model to represent unsafe behaviour, we would be increasing the probability its occurrence.

It is worth noting that any error in the value of *parameters which are supposed to represent policy variables* will mean that the system under test has been incorrectly specified; quite simply the model predictions will not relate to the system of interest. As discussed above, the significance of this miss-specification will depend on the nature of the error and on the way that the model is being used.

Quite clearly, a fundamental contributor to the problems noted above is the concentration on indicators of operational performance and the failure to consider indicators of safety. But this myopia may be difficult to avoid if the model does not produce any indicators of safety. It is to this issue which we now turn.

5.2. Modellers' liability

The preceding discussion has introduced the question of accuracy versus reality. Models are used in the design of elements of the traffic system. If the design of these elements involved assumptions of unsafe behaviour what is the legal liability of the model developer should an accident occur? The design may result in a more efficient traffic movement in terms of travel time, operating cost and environmental impact. However it may require drivers to take unnecessary risks. If a driver takes this risk and an accident occurs the design may be unsafe and the modeller developing the simulation may be seen as liable for the development of an unsafe design.

5.3. Accuracy and stability of existing simulation models

Existing simulation models are built with a set of assumptions. Could these models realistically predict unsafe behaviour, given appropriate parameter values and the delay, which would occur when an incident takes place? It may be necessary to develop a new set of models with more complex representation of behaviour.

The introduction of unsafe behaviour into simulation models could result in the decrease in the stability of models. This may have considerable implications for "convergence" (or number of simulation runs required) if allowance for random aspects of safety are introduced. The use of the models may be made less attractive because of the need for longer run times.

5.4. Potential indicators of safety

It is quite possible to imagine a traffic simulation model being modified in order to predict the occurrence of crashes. Existing sub-models could be enhanced to allow for a wider distribution of driving styles, vehicle characteristics, infrastructure and weather conditions and, when a critical set of conditions came together, a crash could be predicted. The occurrence of a crash could then be allowed to create an obstacle which would interrupt the traffic flow, cause congestion, perhaps inducing secondary crashes ... and so on—a prospect which might well appeal to the creative imagination of the modeller!

However, since crashes are rare events, little practical use could be made of predictions of their occurrence until, in some future time the computing power allows thousands of days to be simulated in a few minutes, the binary occurrence of crashes could be replaced by a probability. In the meantime, allowing a traffic simulation model to predict crashes would bring with it the inconvenience of increased instability in the prediction; the occurrence or non-occurrence of an incident would so dominate the predicted operational performance of the scheme that it would become necessary to increase the number of runs massively. For the foreseeable future it would thus be more useful to predict conflicts or near-misses rather than actual crashes.

This might be done by making use of the concept of the 'time-to-collision' (TTC) between two vehicles (or between a vehicle and a stationary object). TTC is defined as "the time for two vehicles to collide if they continue at their present speed and path" (Sayed et al., 1994). The value of TTC is infinite if the vehicles are not on a collision course; but if the vehicles are on collision course, the value of TTC is finite and decreases with time unless avoiding action is taken (Hoffman and Mortimer, 1996). By logging the occurrence of all TTCs below a critical threshold, an indicator of near-misses could be produced.

An alternative approach, whose attraction lies in the fact that it could be achieved without any reprogramming, might be to output a record of the number occurrences of emergency braking, very low headways or very short gaps. Simulation models have been developed to study the probability and severity of multiple collisions resulting from the abrupt deceleration by a vehicle in a platoon (e.g. Tsao and Hall, 1994; Hitchcock, 1994). The micro-simulation model TRANSIMS was used to estimate the likelihood of accidents in a given network (Ree et al., 2000). Though the TRANSIMS model is collision-free, Ree et al. used the rare hard decelerations that occur when avoiding collisions as an indicator for potential accidents and estimated the probability distributions of accidents in time and space in the network. They assumed that if a vehicle cannot decelerate enough, there will be a collision. Such deceleration events are then combined with accident probabilities (derived from regional accident field data) to calculate the expected number of accidents in a given location and time interval.

However, evidence in a paper by Hallmark and Guensler (1999) suggests that this might not be reliable. Hallmark and Guensler were interested in the possibility of using traffic simulation models to estimate emissions. They compared the distributions of speeds, accelerations and decelerations observed in the field with those predicted for the same sites and traffic flows by the NETSIM model (Rathi and Santiago, 1990) using the default values for speed and acceleration. Some of the default parameters in NETSIM were seemingly too far in the direction of aggressive driving while others were seemingly too far in the other direction. The authors pointed out that, because of the linearity of NETSIM's speed/acceleration relationship, no amount of adjustment of the parameters defining this relationship would have enabled them to reproduce the observed distributions of speed and acceleration. This suggests that, without considerable additional research and development, indicators such as emergency braking, very low headways or very short gaps derived from the current generation of traffic simulation models could only provide crude estimates of the relative scale of the accident potential.

Another issue to consider at this point is that, if indicators of micro-behaviour were to be used as an indication of accident risk, the whole process of fitting the model to observed behaviour would become much more difficult. The current technique, whereby the distribution of aggressiveness in the driving population is adjusted in order to reproduce aggregate indicators such as speed and flow, would clearly be unacceptably simplistic because it would not allow different aspects of aggression to be adjusted differentially. As noted in the preceding section, differences in the scale of 'errors' in the values of different parameters can bias the model's prediction of the relative safety of different types of scheme.

The production of reliable indicators of safety would represent an enormous advance but proxy indicators of safety need to be accompanied by serious health warnings.

6. Concluding remarks

This paper has identified the key parameters of traffic simulation models and noted that the values of several of the key parameters of traffic simulation models have been derived from theory or informed guesswork rather than observation of real behaviour and that, even where they are based on observations, these may have been conducted in circumstances quite different to those which now apply.

We have seen, from tests with the DRACULA model, that predictions of scheme performance are sensitive to the value of safety-related parameters and that sub-optimal investment decisions are likely to result from the use of inappropriate parameter values. We have noted that the bias in the investment decision will depend, not only on the nature of the 'error' in the parameter values, but also on the way in which the appraisal is being conducted and, most crucially, on whether account is taken of safety as well as the operational performance of the schemes. We have concluded in this context that, despite the difficulties inherent in producing reliable indicators of safety from a traffic simulation model, it may be unwise to allow investment decisions to be made without reference to such indicators.

With reference to our original question, (*Is it "right" in a detailed traffic simulation model to use parameter values which represent the actual behaviour of drivers even though this behaviour might be unsafe, or would the use of unsafe parameters contribute to the adoption of unsafe designs?*) we have concluded that, provided that proper account is taken of safety consequences, it will always be better to adopt realistic values of parameters—even if they imply unsafe behaviour. However, if proper account is not being taken of safety indications it is possible that the use of realistic-but-unsafe parameter values could promote the adoption of unsafe design elements.

Given that the answer is not completely clear cut, we must now turn to our second question (*Should ethical issues impinge on the selection of parameter values*?). Public officials have a specific duty to use public funds effectively and a more general duty to further the expressed objectives of the community. An adviser or technical expert is expected to do his or her best to give accurate and unbiased advice. Against this background it is clearly incumbent on the modeller to provide the most accurate predictions possible—and in a behavioural model this implies using the most accurate representation of behaviour that is available. Even though, because it deals with life and death, safety is widely regarded as somehow fundamentally more important than operational performance, it cannot be right for the modeller take it on himself or herself to decide the priority to be put on different objectives. Use of overly safe parameter values would distort the predictions of scheme performance and could lead to sub-optimal decisions. The use of such values may lessen the risk of favouring schemes which offer some advantage to unsafe driving practices, but a better way of achieving the same end would be to provide some indicator of the occurrence of such behaviour and allow this to be taken into consideration during the appraisal.

The calibration process should seek to ensure that the model predictions are as accurate as possible. In this context there must be some concern that the practice of using global parameters such as the distribution of aggressiveness to achieve a match between aggregate indicators of the operational performance of the system may compromise the accuracy with which the model can predict other aspects of system performance.

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