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Microsimulation models incorporating both demand and supply dynamics

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Abstract

There has been rapid growth in interest in real-time transport strategies over the last decade, ranging from automated highway systems and responsive traffic signal control to incident management and driver information systems. The complexity of these strategies, in terms of the spatial and temporal interactions within the transport system, has led to a parallel growth in the application of traffic microsimulation models for the evaluation and design of such measures, as a remedy to the limitations faced by conventional static, macroscopic approaches. However, while this naturally addresses the immediate impacts of the measure, a difficulty that remains is the question of how the secondary impacts, specifically the effect on route and departure time choice of subsequent trips, may be handled in a consistent manner within a microsimulation framework.

The paper describes a modelling approach to road network traffic, in which the emphasis is on the *integrated* microsimulation of individual trip-makers' decisions and individual vehicle movements across the network. To achieve this it represents directly individual drivers' choices and experiences as they evolve from day-to-day, combined with a detailed within-day traffic simulation model of the space–time trajectories of individual vehicles according to car-following and lane-changing rules and intersection regulations. It therefore models both day-to-day and within-day variability in both demand and supply conditions, and so, we believe, is particularly suited for the realistic modelling of real-time strategies such as those listed above. The full model specification is given, along with details of its algorithmic implementation. A number of representative numerical applications are presented, including: sensitivity studies of the impact of day-to-day variability; an application to the evaluation of alternative signal control policies; and the evaluation of

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the introduction of bus-only lanes in a sub-network of Leeds. Our experience demonstrates that this modelling framework is computationally feasible as a method for providing a fully internally consistent, microscopic, dynamic assignment, incorporating both within- and between-day demand and supply dynamics.

Keywords: Microsimulation; Network; Route choice; Variability; Real-time strategies

1. Introduction

Recent years have seen a massive increase in *real-time* advanced technological strategies designed, for example, to reduce congestion, improve network efficiency, promote public transport use, decrease pollution and/or increase road safety. At the network-wide level, these include: responsive, optimised traffic signal control, e.g. SCOOT (Hunt et al., 1981); congestion-based road pricing (Oldridge, 1990); dynamic route guidance/information and variable message signs (Emmerink and Nijkamp, 1999); congestion management strategies, e.g. freeway ramp-metering, gating (Papageorgiou et al., 1989); public transport priority measures such as responsive bus signal controls (Quinn, 1992), bus lanes and guided bus schemes (Liu et al., 1999).

A general property of all these strategies is that they both respond to—and in turn influence—prevailing congestion levels, rather than being designed on the basis of long-term average conditions. That is to say, the variation in traffic conditions is just as important a consideration as the mean. Variabilities include the temporal distribution of flows, as well as the variation in travel times and delays both within and between days. It includes not only *natural* variability associated with normal trip making decisions but also *unnatural* variability associated with incidents or accidents. In order to evaluate these systems and to determine the best strategy for implementation, it is crucial to have a reliable evaluation model that fully incorporates the effects of variability. In addition, since these strategies all must be implemented within the wider transport system, it is important that such an evolution model reflects the *network* effects of any measures.

The analysis of traffic networks has traditionally been based on Wardrop's equilibrium principle (Wardrop, 1952), predicting a long-term average state of the network. Such a model assumes steady-state network supply and demand conditions from day-to-day and within different periods of a day, and therefore has great difficulty in representing the dynamics of the transport systems and many of the above mentioned contemporary transport policies whose major purpose is to deal with variability in demand and network traffic conditions. In addition there is strong evidence that, by ignoring most sources of day-to-day and within-day variabilities, conventional equilibrium models tend to over-estimate network performance and therefore to produce biased results (Mutale, 1992).

Partly in response to these deficiencies, enormous advances have been made in the way in which traffic networks may be modelled. Among which is the advances in the use of microsimulation technique in modelling drivers and driver behaviour in transport networks. By explicitly representing the individual entities, i.e. the people and vehicles, that act and interact in a transport network system, microsimulation modelling provides an extremely flexible framework whereby disaggregated, behaviour-based research can be incorporated and tested.

A large number of traffic microsimulation models have been developed in order to study operational and design problems in road transport systems. Notable among the applications are studies of: *automated highway systems*, such as lane routing (Eskafi et al., 1995; Lee and Lee, 1997), merging control (Ran et al., 1999; Hidas, 2002), ramp-metering (Hasan et al., 2002) and the integrated control of access, lanes and routes (Ben-Akiva et al., 2003); *automatic vehicle control systems* (Chang and Lai, 1997) such as adaptive cruise control (Marsden et al., 2001; Suzuki and Nakatsuji, 2003) and intelligent speed adaptation (Liu and Tate, 2004); *traffic management measures*, ranging from bus priority schemes (Quinn, 1992; Liu et al., 1999) to tollbooth design (Huang and Huang, 2002), pedestrian facility design (Liu et al., submitted for publication) and responsive traffic signal systems (Kosonen, 2003; Niittymäki and Turunen, 2003; Bullock et al., 2004); *Incident Management Systems* including incident recognition (Mussa et al., 1998), incident detection (Khan and Ritchie, 1998; Sheu, 2004), and incident response strategies (Sheu and Ritchie, 2001; Cova and Johnson, 2003); *real-time driver information systems* (Hu and Mahmassani, 1997; Dia, 2002; Adler et al., 2005; Rossetti and Liu, 2005); *traffic flow stability analysis* (Chakroborty and Kikuchi, 1999; Huijberts, 2002; Davis, 2003; Bham and Benekohal, 2004); and the *prediction of environmental impacts*, including exhaust emissions (Yu, 1998), energy consumption (Ambrosino et al., 1999), and safety (Köll et al., 2004).

It is noticeable that a great majority of these applications have focused on problems of a short-term forecasting nature, where microsimulation is able clearly to demonstrate its advantages over static, macroscopic approaches in estimating the *immediate* traffic flow impacts of some measure. However, in the present paper we are particularly interested in the potential for microsimulation as a medium-term transport planning tool. In this latter case, it is crucial to consider the *secondary* effects[1] caused by drivers changing their travel decisions on subsequent trips in response to their new experiences of traffic conditions. Thus, for example, the implementation of a new responsive traffic signal system at an intersection may lead to reduced delays in the short term, but in time (over a period of days and weeks) this may lead to traffic diverting from alternative routes or changing their time of trip departure, leading to a medium-term change in the magnitude and profile of the flows that impinge on that intersection. In spite of all the criticisms of the static equilibrium paradigm, it is the ability of such an approach to deal with both the immediate and secondary effects that has led to its popular use in transport planning. If microsimulation is also to take its place as a mainstream approach to transport planning, it must be able to address such secondary effects.

How have microsimulation approaches been used to address these secondary effects? Three main approaches may be identified. In the *first approach*, the secondary effects are neglected (e.g. Laird et al., 1999). This might lead one to conclude that, therefore, no secondary effects will occur in the model, but this may not be quite true. In particular, if the microsimulation input data requires turn probabilities to be input at each intersection (rather than, say, complete routes to be defined), then 'routes' are implicitly reconstructed by making Monte Carlo draws for each vehicle according to these turn probabilities. If some control measure is then applied which affects the sequencing of vehicle arrivals, then there will be an impact on the sampled turn *proportions* due to the effective change in sequence of the random numbers generated. Thus, even though no behavioural model is supplied to represent the secondary effect, an apparent effect may occur simply due to Monte Carlo noise. It is difficult to justify such an impact as desirable, since the

[1] The term 'secondary' is not meant to infer that these effects are in some sense less important, but rather that chronologically they occur after (and as a result of) the immediate impacts.

modeller has no control over it, and indeed both anecdotal and theoretical evidence exists to suggest that such turn-based definitions may lead to implausible cycles (vehicles re-visiting the same link a number of times) of arbitrary length (Akamatsu, 1996).

In the *second approach*, the secondary effects are predicted by using a coarser model which is either run once in stand-alone mode prior to the microsimulation (for example, Montero et al., 2001, propose the use of a static equilibrium model, with the equilibrium turning fractions then input as turn probabilities to the microsimulation), or is based on some aggregated feedback loop from the microsimulation (Fellendorf and Vortisch, 2000; Barceló and Casas, 2004). In neither case are the secondary-level decisions made on the basis of consistent assumptions and aggregation levels with the microsimulation, and so one is open to the same criticisms levelled at the static equilibrium approaches.

The *third approach* is to use some consistent mechanism to feedback the travel experiences at the microscopic level and simulate individual trip choices (Liu et al., 1995; Nagel and Barrett, 1997; Hu and Mahmassani, 1997). In this approach, then, one effectively defines a dynamic process that explains drivers' day-to-day learning and trip-to-trip travel choice adjustments. A further advantage of this approach is that one can avoid the problems of turn-probability based definitions (noted above), by requiring the day-specific inputs to the microsimulation to be *complete paths* traversed at particular departure times, the paths and departure times both being selected by the dynamic process model explaining the day-to-day adjustments. The price paid for such an approach is, however, a much more complex model to interpret, with complex issues of convergence, stability and even existence of attractive states to handle.

In spite of these latter comments regarding model complexity, it is our belief that the third approach noted above is the most appropriate for taking microsimulation into mainstream transport planning, since it offers both an integrated (single model) and consistent (all decisions and experiences made at individual level) approach to the problem. This paper describes a particular model framework based on such an approach. The model, code named DRACULA (Dynamic Route Assignment Combining User Learning and microsimulation), integrates a microsimulation of individual drivers day-to-day learning and route choice model with a traffic microsimulation model of the car-following and lane-changing nature. In combination they model the evolution of the traffic system over a representative number of days so that both within-day and between-day variabilities are included.

The structure of the paper is as follows. The general structure of the DRACULA microscopic framework of day-to-day dynamic network models is introduced in Section 2. The methodological and algorithmic aspects of the day-to-day evolution model (Section 3) and the within-day traffic simulation model (Section 4) are then described in detail. A brief description of the DRACULA software design and implementation is given in Section 5. Potential applications of such a model framework and demonstrations of its applicability in tests of realistic policy measures are given in Section 6, followed by concluding remarks (Section 7).

2. DRACULA model structure

As with conventional equilibrium models the DRACULA approach begins with the concept of demand and supply (or performance) sub-models that interact with each other. However, by contrast with conventional models, in DRACULA both the demand and supply sub-models are based on microsimulation and both evolve from day-to-day. In DRACULA, trip makers are individually represented and their daily route choices (demand) are made based on their past experience and their perceived knowledge of the network conditions. Individual vehicles are then moved through the network (supply) following their chosen routes according to rules governing car-following, lane-changing and intersection control. The demand stage predicts the level of individual demand for day n from a full population of potential drivers and the supply model for day n determines the resulting travel conditions. The costs experienced by drivers are then re-entered into their individual *knowledge bases* which in turn affect the demand model for day $n+1$. The process continues for a pre-specified number of days. The overall structure of the framework and the interaction among its various sub-models are illustrated in Fig. 1.

The framework combines a number of sub-models of traffic flow and drivers' choices for a given day with a day-to-day driver learning sub-model. In its most general form it has the following structure although, as we shall discuss later, certain alternative methods or simplifications are possible within most stages.

1. [Input data] Load data on network representation and origin–destination trip matrix.
2. [Population generation] Establish a population of potential drivers with individual characteristics.

Day-to-day (demand) loop:

3. [Initialisation—Part I] Set initial driver perceptions for each link in the network. Set day counter $k = 1$.
4. [Daily demand] Select the total day-k demand for each origin–destination pair according to some given probabilistic rules.
5. [Departure time choice] Individuals travelling on the day adjust their departure time to travel based on previous experience.
6. [Route choice] Each individual travelling on the day chooses a route based on their current perception of traffic conditions and previous experiences. The travel time component of the cost is based on the individuals' departure time and their predicted arrival times at each link/turn.
7. [Supply variability] Select *global* network supply condition for day k prior to loading by some given probability laws to simulate effects such as weather and lighting conditions. *Local* variations in network conditions (such as road works, incidents occurring on the day) are also specified.

Within-day (supply) loop:

8. [Traffic loading] A microscopic simulation of traffic conditions on day k is carried out given the choices and supply variability above. Drivers experience within-day variable link and turn travel times for the route and departure time they have chosen.
   (a) [Initialisation—Part II] Set within-day simulation clock $t = 0$.

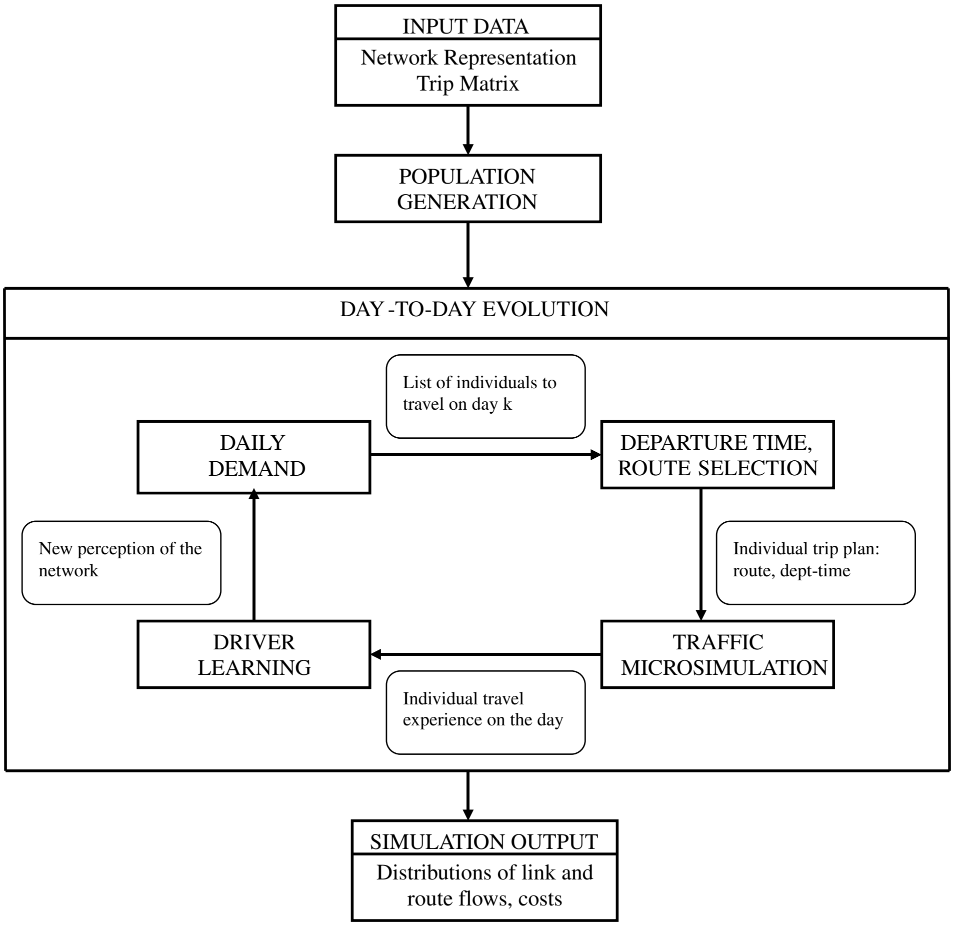

Fig. 1. DRACULA model structure.

(b) [Vehicle generation] Vehicles enter the network at their chosen departure time. Each vehicle is assigned a set of individual characteristics.
(c) [Vehicle movement] Each vehicle follows the pre-specified route. Their speeds and positions are updated according to car-following, lane-changing and gap-acceptance rules, and traffic regulations at intersections.
(d) [Traffic control update] For each signalised junction, update the stage change-over clock according to desired signal plans (fixed plans or responsive). Check if any incident is to start or to finish.
(e) [Data collection] Individual drivers' experience within-day are stored. Aggregated measures such as queue length, travel time, speed, flow, emissions, fuel consumption are recorded for every turn, link, route, and O–D pair, and for the whole network.
(f) [End of day] If all drivers have finished their journey, terminate the day; otherwise increment the simulation clock and return to step 8b.

9. [Learning] At the end of day k, drivers update their perceptions based on their experiences of link and turn travel times on the day.
10. [Stopping test] If some stopping condition is satisfied, terminate; otherwise increment the day counter and return to step 4.

Note that this process will not converge to a single equilibrium point but will continue to vary from one day to the next. Instead, our objective is to determine the probability distribution of individual day-to-day states, appealing to the theory of stochastic processes (Cascetta, 1989; Cantarella and Cascetta, 1995; Watling, 1996; Hazelton and Watling, in press).

Similar models of this day-to-day structure have been considered previously by Alfa and Minh (1979), Ben-Akiva et al. (1986), Vythoulkas (1990), Emmerink et al. (1994), Nagel and Barrett (1997), Hu and Mahmassani (1997), though generally with the day-to-day evolution represented as a deterministic process, with the aim to converge to a fixed point.

Details of the functionality of steps 2–7 and step 9 are discussed in Section 3. Section 4 introduces the traffic microsimulation model used in step 8.

3. Day-to-day evolution of travel demand and network conditions

3.1. Modelled population

In principle, the modelled population can include all the potential drivers in the study area. Each individual member of this population has certain characteristics (such as household origin, work place, car-ownership status, driving style, etc.) and a *history file* in which the accumulated experience of previous choices and travel conditions encountered is stored. Equally the vehicle they drive will have certain fixed characteristics such as vehicle size and engine type which do not change from day-to-day. As far as feasible the distribution of characteristics should match as closely as possible that of the area being modelled.

In practice, however, simplifications and compromises will need to be made. More pragmatically therefore we aim at generating a population whose trip making behaviour at the aggregate day-to-day level matches the averages and variances observed in real life. In our applications, the population is derived from an existing conventional trip matrix T_{ij} from origin i to destination j. We then assume (see also Section 3.2 below) that the day-to-day variability in the number of trips may be described by a normal distribution whose mean is T_{ij} and whose variance is $\beta_{\mathrm{d}}^2 T_{ij}^2$ where $\beta_{\mathrm{d}} > 0$ is a user-set coefficient of demand variation. Hence the demand for ij trips on day k is:

$$t_{ij}^{(k)} = Nor(T_{ij}, \beta_{\mathrm{d}}^2 T_{ij}^2) \quad \text{(truncated at zero)} \tag{1}$$

We define our population of potential ij travellers to be $T_{ij}^{\max}$, the pragmatic maximum number of trips generated by Eq. (1). Although the maximum of Eq. (1) is effectively infinite, in practice we use:

$$T_{ij}^{\max} = T_{ij} + 3\beta_{\mathrm{d}} T_{ij} \tag{2}$$

By default, each driver's choice on the first day of travel is based on average free-flow travel times, and for each link and turn the perception is unchanged until that link or turn is used by the individual. However the initial choices may also be specified to be those resulting from a previous model run. The most obvious application of this is in a before-and-after study of a scheme, in which the initialisation of the 'after' run is based on the final conditions of the 'before' run. Similarly, the initial *histories* of drivers—i.e. their remembered experiences on the network—may be set to be their accumulated experiences in the previous run.

In addition to *drivers*, the modelled population also includes elements such as buses following fixed routes, for which clearly route choice and a *knowledge base* are not issues. They will, however, require their own appropriate vehicle characteristics.

3.2. Day-to-day demand

On any particular day within the evolution of the model each member of the population makes a decision as to whether to travel or not. In principle the decision could—and should—be based on the individual characteristics of that member of the population, so as to differentiate between regular commuters and one-off shopping trips and to include elements of their knowledge base. In practice a more pragmatic approach has been used whereby individual decisions are constrained by the predicted daily trips for their particular origin–destination pair.

Thus for each origin i and destination j we:

(1) select the mean demand level appropriate to day k, denoted $t_{ij}^{(k)}$, from Eq. (1);
(2) form the probability $p_{ij}^{(k)} = t_{ij}^{(k)}/T_{ij}^{\max}$;
(3) each potential traveller then independently chooses to travel on day k with probability $p_{ij}^{(k)}$.

Note that clearly, any reference to drivers' histories or choices made during the simulation relates to the fixed pool of potential travellers who keep their identification through the simulation, rather than the day-to-day varying pool of individuals who actually make a journey through the network.

A generalisation of this method is also permitted, in which different *user classes* are defined, which differ only in their propensity to travel (representing, for example, shopping trips which may be made less frequently than journey-to-work trips).

3.3. Departure time distribution

The choice of departure time within DRACULA may be handled in a number of different ways. The default and simplest method is to randomly assign a desired departure time for each potential driver in the modelled population according to some departure time profile. When drivers choose to travel on day n they will depart at their desired departure time, independent of their experience and route choice. The departure time profile could be flat or distributed probabilistically according to some user-specified distribution, for example, a step function over time slices.

A more complex departure time choice in response to travellers' experience has also been incorporated within DRACULA whereby departure time selection takes place at the start of every day based on a traveller's preferred arrival time and on the previous day's experiences (anyone not travelling on the previous day will keep the same preferred departure time). A simple continuous adjustment is made for each individual m on each origin–destination movement i–j in turn, based on that individual's:

(a) preferred arrival time at the destination, a_{ijm};
(b) trip time from the previous day $t_{ijm}^{(k)}$; and
(c) departure time on the previous day $d_{ijm}^{(k)}$.

For example, a_{ijm} could be randomly drawn at the start of the simulation from a specified time profile as in the first method.

The difference between the desired and actual arrival time on day k is then:

$$\delta_{ijm}^{(k)} = d_{ijm}^{(k)} + t_{ijm}^{(k)} - a_{ijm}^{(k)} \tag{3}$$

The driver is assumed to (independently between days and from other drivers) be indifferent to a lateness of $e_m t_{ijm}^{(k)}$, which is modelled as in proportion to the actual travel time. The proportion e_m for individual m is drawn from a uniform $[0, \varepsilon]$ distribution, where ε is a user-defined maximum lateness tolerance factor and an $e_m = 0$ means zero tolerance to lateness. Hence, we define the perceived lateness as:

$$\Delta_{ijm}^{(k)} = \delta_{ijm}^{(k)} - e_m t_{ijm}^{(k)} \tag{4}$$

If $\Delta_{ijm}^{(k)} > 0$, the users adjust their departure time so that the perceived lateness would be zero if yesterday's trip time were repeated, then,

$$d_{ijm}^{(k+1)} = d_{ijm}^{(k)} - \Delta_{ijm}^{(k)} \tag{5}$$

Otherwise,

$$d_{ijm}^{(k+1)} = d_{ijm}^{(k)} \tag{6}$$

Thus, in the model described, no early arrival correction is made, but this is readily incorporated by setting $d_{ijm}^{(k+1)}$ according to Eq. (5) regardless of the sign of $\Delta_{ijm}^{(k)}$. The flexibility of the framework enables a more general departure time choice to be implemented easily at a later stage.

3.4. Route choice

By default, each driver travelling on a particular day chooses their minimum perceived generalised cost route based on the traditional concept of utility maximisation that underlies virtually all current traffic assignment models. The key difference is in the concept of *utility* or *cost* which is now an attribute that evolves and varies over days. At the start of any day, each individual forms a perceived cost at a linear combination of relevant attributes (travel time, distance, generalised cost, tools, etc.). For those attributes that are not static, primarily travel time, the travel time used for each link is the one that emerges from the learning process described in Section 3.5 based on that driver's individual history.

An alternative choice model implemented in DRACULA is the *boundedly rational choice*, based on the work of Mahmassani and Jayakrishnan (1991). This model assumes that drivers will use the same (habit) route as on the last day in which they travelled, unless the cost of travel on the minimum cost route is *significantly* better than that on their habit route. The threshold is that a driver will use the same route unless:

$$C_{p1} - C_{p2} > \max(\eta C_{p1}, \tau) \tag{7}$$

where C_{p1} and C_{p2} are costs along the habit and the minimum cost routes respectively, η and τ are global parameters representing the relative and the absolute cost improvement required for a route switch.

These rules are only intended as an example of the range of rules that could possibly be implemented in a flexible approach such as DRACULA. Alternative behavioural rules that could be provided in the future include the concept of risk minimization, with drivers perceiving cost variances as well as means.

The route choices are made and fixed before the trips start; drivers follow their chosen routes through the network to their destinations and will not (within the current state of model development) make en-route diversion when, e.g., encountering congestion.

3.5. Learning

After each journey individuals use their experienced travel times on the links used on that journey to update their perceived link travel times according to the following conditions:

(a) experiences more than M days old are forgotten; and
(b) the perceived travel cost is the average of (at most) the last N remembered experiences on that link.

Here M and N are global parameters set at the start of simulation, although their effect will be specific to each individual's experience. It may reasonably be argued that these parameters should be allowed to vary with the driver and/or trip type, and indeed this may be incorporated in the framework described.

Generally, it is expected that N will be the main parameter affecting perceived cost; M is intended mainly as a device for drivers to ultimately forget a single bad experience of a link which may occur particularly in the atypical, initial warm-up days. Therefore, it is expected that $N < M$.

3.6. Supply variability

The effect of day-to-day variability in network conditions is represented at two levels. The *global variability* represents the effects of weather, daylight, etc., on the network. It is represented in the model by a variable link cruise speed drawn from a normal distribution whose mean is V_l and whose variance is $\beta_s^2 V_l^2$ where $\beta_s > 0$ is a coefficient of global supply variation. Hence the cruise speed for link l on day k is:

$$v_l^{(k)} = Nor(V_l, \beta_s^2 V_l^2) \quad \text{(truncated at a minimum speed)} \tag{8}$$

Local variability is in the form of incidents (e.g., breakdowns or road closures) which may occur one day but not another. This is represented before loading by specifying the location and duration of the incidents.

The global and local variabilities will affect the travel times of vehicles travelling on that day (through the traffic simulation described in the next section), but not on the individuals' routes and departure time choices.

4. The traffic simulation

The traffic model in DRACULA is a microscopic simulation of the (pre-specified) individual vehicles' movements through the network. Drivers follow their pre-determined routes and *en-route* encounter signals, queues and interact with other vehicles on the road. A large number of such microscopic vehicle models have been developed in the past at varying levels of complexity and network size (e.g. in some the network is effectively a single intersection)—see a review by Algers et al. (1997). An essential property of all such models is that the vehicles move in real-time and their space–time trajectories are determined by, e.g., car-following and lane-changing models and junction controls such as signals.

The traffic simulation model developed for DRACULA is based on fixed time increments; the speeds and positions of individual vehicles are updated at an increment of 1 s. Spatially, the simulation is continuous in that a vehicle can be positioned at any point along a link. The simulation starts by loading the simulation parameters, network description including global and local variability and trip information (i.e. the demand and routes determined by the demand model). It then runs through an iterative procedure at the pre-defined time increments, within which the tasks in steps 8(a)–(f) described in Section 2 are performed.

4.1. Network representation

The network is represented by nodes, links and lanes. A node is either external, where traffic enters or leaves the network, or an intersection. All major UK intersection types are modelled; these include priority give way, traffic signal controlled intersections, roundabouts, and fully or partially signalised roundabouts. A link is a directional roadway between two nodes and consists of one or more lanes. A link is specified by its upstream and downstream nodes, cruise speed, number of lanes, and turns permitted to other outbound links from the downstream node. Vehicles move in lanes and follow each other according to the car-following rules. They travel through intersections along *inter-lanes* which are smoothed curves connecting the inbound and outbound lanes. The crossing point of two inter-lanes is a conflict point. Various access restrictions such as one-way streets and reserved lanes, and geometric designs such as flared approach to intersections (where an approach is widened into separate turning lanes) are represented.

4.2. Vehicle generation

Vehicles are individually characterised, including a technical description of the vehicle (vehicle type, length, maximum acceleration and deceleration capability) and behaviour of the driver (reaction time, stopping distance headway, acceptable time gap, desired speed, desired acceleration and deceleration). These characteristics are randomly sampled from truncated normal distributions representative of that type of vehicle:

$$P_u = Nor(P_u, \beta_v^2 P_u^2) \quad \text{(truncated at } P_u^{\min} \text{ and } P_u^{\max}\text{)} \tag{9}$$

where p_u is a random variable representing vehicle parameter p for vehicle type u. P_u, $P_u^{\min}$ and $P_u^{\max}$ are the mean, lower and upper bounds of the distribution respectively. β_v is the user-defined coefficient of variation of vehicle characteristics which can be made vehicle-type specific. For example, there may be greater variability in car drivers' desired speed and acceptable gap than those of drivers of large goods vehicles. The characteristics for each vehicle are chosen at the start of a simulation run and they remain the same for the same vehicle from one day to the other. Public transport vehicles are represented with additional information such as service number, service frequency, bus stops *en-route* and passenger demand (Liu et al., 1999).

The default values (as used in the numerical results reported in Sections 6.3–6.5) are based on a number of sources including May (1990), Institute of Transportation Engineers (1982), Gipps (1981). A discussion on the choice of parameter values for microsimulation models and their impact on model results is presented in Bonsall et al. (in press).

4.3. Vehicle movement

Vehicles are moved in real-time and their space–time trajectories are determined by their desired movements, response to traffic regulations and interactions with neighbouring vehicles according to car-following and lane-changing rules and simulation of conflicts at intersections. A detailed description of the vehicle movement simulation model incorporated in DRACULA can be found in Liu (2005). The key driving behaviour modelled is presented below.

4.3.1. Car-following model

The car-following model represents the longitudinal interactions among vehicles in a single stream of traffic. It calculates the following vehicle's speed and acceleration in response to stimulus from the preceding vehicle. Depending on the relative distance to the preceding vehicle, the following vehicle is assumed to be in one of three different following regimes: free-moving, normal following, or close-following.

When a vehicle is the leading vehicle in a platoon, or is long way away from its downstream intersection, it is assumed that the vehicle can accelerate or decelerate *freely* in order to maintain its desired speed.

When the space headway becomes shorter, the following vehicle will enter the *normal following* regime and will take a controlled speed derived from a linear function of the relative speed and distance to the preceding vehicle. When the space headway gets very small and the vehicle is described as in *close-following* regime, the driver will prepare to stop in case the preceding vehicle brakes suddenly. A stopping distance based car-following model as proposed by Gipps (1981) is used here to describe such close-following regime.

4.3.2. Lane-changing model

The model firstly identifies the reasons for a lane-changing desire. The following reasons or types are considered:

(a) bus stopping at bus stops;
(b) avoiding an incident (e.g. accidents, road works, parked vehicles);
(c) making junction turning movement at the immediate downstream intersection;
(d) moving into a lane reserved for their type, or avoiding a restricted-use lane;
(e) gaining speed by overtaking a slower moving vehicle;

(f) giving way to a merging vehicle or to a bus merging from a bus lay-by; or
(g) anticipating a lane-changing need of type (a), (c) or (d) in a downstream link.

The first three types are *mandatory*, i.e. the lane-changing has to be carried out by a certain position on the current link, for example the location of the bus stop. The other types are *discretionary;* whether such a discretionary lane-changing can be carried out depends on the actual traffic conditions. For example, a vehicle would only change lane to gain speed if the speed offered by the adjacent lane is *significantly* higher than that on their current lane. The threshold is a behavioural variable that can be calibrated to the observed local behaviour.

Once a lane-changing desire is triggered and the target lane selected, a gap-acceptance model is used to find the gaps in the target lane which are acceptable to the driver wishing to change lanes. A variable critical gap is modelled to reflect the phenomenon of impatient drivers for whom the critical gap decreases with each passing gap (e.g. Kimber, 1989; Taylor et al., 2000). The stimulus required to induce the decrease of critical gap is modelled as the time spent in searching for acceptable gaps. A minimum gap is used to set a lower boundary to the gap-reduction formulation.

4.3.3. Intersection simulation

In the model, vehicles start to react to traffic controls (traffic signals or give way sign) at a downstream intersection when they reach a certain distance d^s to the intersection. d^s is used to represent both the physical sight distance to the intersection and the sensitivity of drivers to intersection control. Only the lead vehicle in a platoon reacts to intersection control; the following vehicles follow the preceding ones according to car-following rules until they become the lead vehicle.

At traffic signal controlled intersections, the model tries to take into account some of the unsafe driving behaviour such as adopting a smaller headway when passing through the green phase, passing traffic signals at amber or even at the start of red. The right-turning (for drive on the left) vehicles (the number of these vehicles is dependent on the size of the junction) who needs to give way to opposing straight-ahead vehicles can wait into the middle of the junction for a gap to cross.

For a give way intersection, the model uses a visibility parameter to represent the geometric openness of a junction and to model the phenomenon whereby, instead of stopping by the stop line, some drivers may even accelerate to join in or to cross the major flow if they can see the situation on the major road. The critical gap decreases as the time a driver spent waiting for an acceptable gap increases.

Unlike the common method of representing roundabouts as series of one-way links, the model represents a roundabout as a single node with a circular link around it. Vehicles approach a roundabout as though approaching a priority junction: get into the correct lane for its junction turning and give way to circulating traffic on the circular link.

4.4. Simulation outputs

To measure the performance of a network, the simulation provides summary statistics on the link-, OD- and network-wide averages and variances in travel time, speed, queue length, fuel consumption and pollutant emission, over regular time periods. The most detailed records are the second-by-second individual vehicles' locations and speeds. The model also provides point- or loop-based detector measures on headway distribution, flow, occupancy and speed. For each bus service, the model summarises the means and variances of total journey time and journey time between stops; these measures can help distinguish service delays due to traffic congestion from those due to poor management. A graphical animation of the vehicles' movements can also be shown in parallel with the simulation, giving the user a direct view of the traffic conditions on the network.

A clear distinction is made between the performance of a network and costs associated with a given demand (Liu, 2005). The performance of a network or a single link can be measured in terms of vehicle-km and vehicle-hour travelled in a defined period. These are the engineering descriptions of the performance of the link or a network at a given point in time or over a given time period, and can be used to estimate the link or network equivalent of speed–flow relationships. The performance measures can be obtained by dividing the simulation period into a number of equal performance periods and aggregating the parts of the vehicle trajectories within each period.

The supply costs reflect the costs experienced by a driver using the network at a given level of demand; they can be used to describe the way in which costs of using a network rise as demand-levels increase. Since any journey through a network will pass through a number of different traffic states and the costs incurred will be affected by both the journey length and the route taken, as well as by the impacts of other demands on the network both at that time and in earlier time periods. In order to measure these costs, individual vehicles need to be *tracked* through the network and their origin–destination trajectories summarised. The summation can be done either over a *departure time period* or an *arrival time period* where all vehicles departed or arrived during the period respectively are summarised. In DRACULA the departure time aggregated supply measures are recorded.

5. Implementation

DRACULA has been developed as a flexible framework through modular implementation of its sub-models. We described in Sections 3 and 4 the most general formulation of the demand and supply models. At its most detailed level, DRACULA represents individual drivers' day-to-day choice making processes and individual vehicles' movements through a network; this version of the model is hereafter called the *full model*.

In practice, however, it may be desirable to run the model with a number of simplifications. Thus, the traffic supply model may be based on a more conventional static network model with macroscopic flow–delay functions but with variable parameters such as link capacity, while the demand model is based on the full evolution of driver choices from day-to-day. An application of the latter approach is described in Section 6.2.

Similarly the demand route choice can be derived from a static equilibrium assignment, but applied to the vehicle-by-vehicle simulation. We have developed a link with an existing equilibrium model SATURN (van Vliet, 1982) in that the SATURN network data can be used by DRACULA and the equilibrium route assignment and link costs from SATURN can be used as the initial histories of the drivers simulated by DRACULA. The microsimulation models require

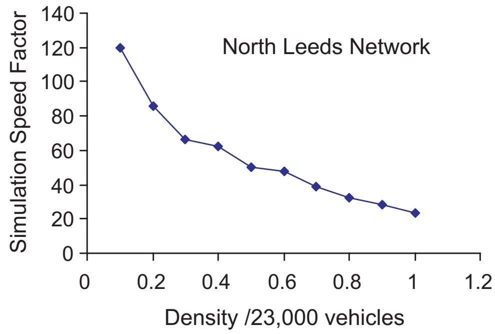

Fig. 2. Simulation speed factor versus traffic density.

essentially the same basic network data as a mesoscopic simulation model such as SATURN—nodes, links, number of lanes per link, lane markings, signal operations, give way rules, etc., with some extra data related to the geometry and size of intersections for example. The links with existing models is very useful for microsimulation models, in that it helps bring microsimulation modelling to the traditional network modellers with relative ease. The development, testing and application of microsimulation models can also benefit greatly from the large data bank of existing modelled networks.

The flexibility of the framework ensures that, while keeping its novel aspects in one way or the other, DRACULA can be integrated to a greater or a lesser extent into existing models. Current data bases will almost certainly provide the best starting points for new models.

The computer implementation of the model framework imposes no limitation on the size of the network or the demand level. The processing speed does not appear to be affected significantly by the size of a network, but decreases with the number of vehicles in the network increases. The processing speed improves significantly if the graphical animation of the simulation is switched off. Fig. 2 illustrates the simulation processing speed (measured as the ratio of the time simulated to CPU time), without animation, as a function of traffic density in a network using a Pentium II-300 PC. The network is the north Leeds network described in Section 6.5. It can be seen that the processing speed decreases exponentially as flow density increases. Even at the full demand (23,000 vehicles/hour) the simulation ran 20 times faster than real time. This shows therefore that this modelling framework is computationally feasible as a method for providing a fully internally consistent, microscopic model of both demand and supply dynamics.

6. Applications

6.1. General

While in theory DRACULA could be applied to studies of long term and large scale network changes, such as the construction of new motorways or a bypass, this is an area where conventional aggregate equilibrium models are likely to be satisfactory (although the difficult question of demand responses such as departure time changes arises even here). However the behaviourally sounder microscopic models could be used to test certain key assumptions of macroscopic models, and to suggest alternative methods (possibly empirical modifications) which might improve conventional techniques.

It is in the general area of testing real-time policies that we feel the use of microscopic models to be essential. For example it is an ideal environment for a detailed simulation of responsive signal control systems (such as SCOOT), including the potential effects on driver re-routing. Similarly it can be used to model congestion pricing schemes such as those proposed by Oldridge (1990) where the charge—if any—is determined by the precise space–time trajectory of individual vehicles. In addition disaggregate demand models, in which each individual's propensity to pay for travel may be represented, offer a sounder behavioural basis than aggregate models.

A key feature of the model is its ability to consider multiple classes of users, which may differ in one or more of the following characteristics:

(a) informed or non-informed, and the nature of information available;
(b) speed-control equipped or not;
(c) behavioural response rules;
(d) traffic performance characteristics (length, acceleration, deceleration, risk);
(e) vehicle types which determine their access to physical facilities (such as bus lanes, HOV lanes and guideways for guided buses).

Finally, it offers an opportunity to measure variability within a modelling framework. Variability in journey time reliability is an issue which is probably felt to be crucial by most commuters but generally disregarded by most models.

Next we present some results from applications of DRACULA in studying the variability effect, in modelling dynamic systems on drivers' route choices and system performances, and in scheme evaluation. The results and discussion are primarily intended to illustrate the applicability of the DRACULA approach, and to show that the model responds logically to changes in model parameters.

6.2. Day-to-day variability (simplified model)

In this section, as a precursor to the main model results, we report the qualitative findings of applying a simplified DRACULA model, in order to indicate the sensitivity of the model predictions to day-to-day demand and supply variability. A highly simplified traffic model is used, with a static flow–delay relationship for each link and no junction-based delay. In particular, below capacity travel time is assumed to increase with flow according to a power-law, with delays increasing linearly above capacity according to deterministic queuing theory.

On the demand side, the full evolution of driver choices from day-to-day (as described in Section 3) is modelled. On the supply side, link capacities vary randomly (according to a uniform distribution) from day-to-day to simulate crudely the effect of parking, accidents, etc.

Preliminary tests with the above model have been performed on a number of networks, ranging from small artificial ones to a real-life network containing some 440 links and 20,000 individual trips on average per day. Because neither the method of generating the variability, nor the actual levels of variability assumed, were calibrated from real-life data, the work was considered to be more of a sensitivity analysis. For this reason, it is not appropriate to report absolute figures. Instead, the general themes arising from the tests are reported. These will serve as hypotheses, to be tested in the next sub-section on different scenarios.

Stability of the model was examined by comparing day-averaged link flows and travel times from runs with different numbers of total days simulated, different numbers of *warm-up* days discarded, and different pseudo-random number seeds. In addition, successive n-day-average flows were compared ($n = 10$) as a measure of 'stability'. Different networks tended to need a different number of days to stabilise to the same level, although 50–100 was generally found to be adequate. The apparent stability was verified by comparing runs with different random number seeds, where it was confirmed that the differences in mean flows were attributable purely to sampling variation.

The general findings were:

(a) As might be expected, link flow variances generally increased with a decrease in the behavioural parameter M (see Section 3.5) over the range tested from 5 to 20. Provided M was somewhat less than the number of (non-warm-up) days simulated, mean flows were not greatly affected. For large values of M, certain pathological cases existed where single very bad experiences in early days had a significant effect on final flows.
(b) When the behavioural parameter N (Section 3.5) was set to 1 (all drivers unfamiliar with the network), the model produced unstable—and perhaps implausible—flows for long periods. However, for larger values of N ($3 \leqslant N \leqslant 10$) this instability was not evident. The mean flows did not vary greatly with N in this latter range.
(c) Increasing the variability in OD demand was found to increase the variance in link flows, though it did not substantially affect mean flows. For $3 \leqslant N \leqslant 10$, these mean flows were found to be well-approximated by a deterministic equilibrium model applied to the average OD matrix.
(d) Variability in capacity, when applied to certain critical links, was found to have the greatest effect on long-term mean flows, these being rather different to the equilibrium prediction from average capacity values.
(e) Generally, even in cases where equilibrium and mean day-to-day flows were similar, the former model consistently under-estimated average total travel time in the network (as expected—see Cascetta, 1989; Mutale, 1992).

6.3. Day-to-day variability (full model)

In this section, the full day-to-day model was used to study the effects of demand and supply variability on network performance. The full model, which contains the main features listed in Sections 3 and 4, was applied to a real-life network with some 50 links and 2500 individual trips in a 1-h morning peak. Six simulation tests were conducted with various level of variability in day-to-day demand and network supply conditions (including vehicle characteristics). The detailed parameter settings are listed in Table 1. For each test a total of 100 days were simulated.

Fig. 3 shows the day-to-day total vehicle travel times (in vehicle-hours) over the 100 days simulated for tests 1–4. It demonstrates a general feature of the model: the results do not converge to

Table 1
Coefficient of variances used in the simulation tests

Test number	β_d	β_s	β_v
1	0.05	0.05	0.05
2	0.10	0.10	0.10
3	0.15	0.15	0.15
4	0.20	0.20	0.20
5	0.05	0.20	0.20
6	0.20	0.05	0.05

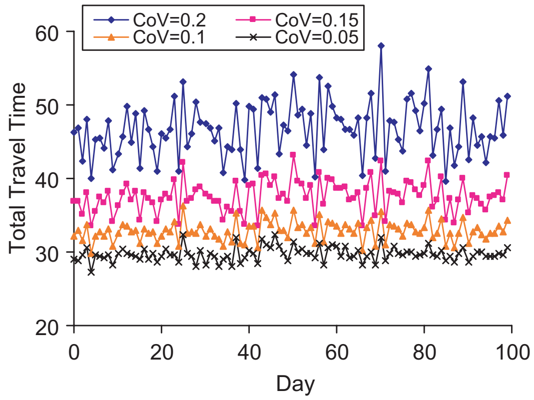

Fig. 3. Daily network total travel time (in vehicle-hours) over 100 days simulated under variable demand and supply conditions. Four levels of coefficient of variation (CoV = 0.5, 0.1, 0.15 and 0.2) are introduced to both the day-to-day demand (β_d) and the supply (β_s and β_v).

a single equilibrium state but continue to vary ad infinitum. Fig. 4 compares the relative impacts of demand and supply variability on the averages and variances in daily vehicle travel times; the comparison is made under the assumption that a demand variability range of $0 < \beta_d < 0.2$ is comparable to a supply variability range of $0 < \beta_s + \beta_v < 0.2$. Both Figs. 3 and 4 show that the day-to-day total vehicle-hours are much higher on average at higher variability than at lower variability. More specifically Fig. 4(a) shows that the demand variability on its own does not substantially affect the *average* travel times, most of the increases being due to supply variability. However, the demand variability introduce greater *variation* in day-to-day travel times than does the supply variability (Fig. 4(b)). This implies that a network becomes more unreliable as the demand variation increases.

A further study was carried out on the network, with β_d, β_s, and β_v all being set at 0.2 and a total of 1000 days being simulated. Fig. 5 shows the frequency distribution of total network travel times by day over the 1000 days simulated. It can be seen that the distribution is skewed towards higher travel times, illustrating the existence of a small number of days with very high total travel time. These days, although relatively few, have a significant impact on the average result since they are not compensated by days with extremely small total travel time. Thus the mean travel time of 98.6 is significantly greater than the mode of 88.7 and the median of 95.0.

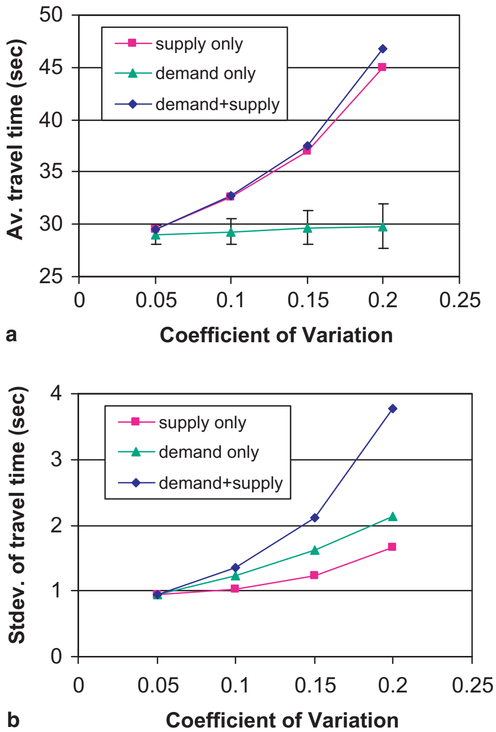

Fig. 4. Average (a) and standard deviation (b) in daily travel times as a function of demand and supply variability.

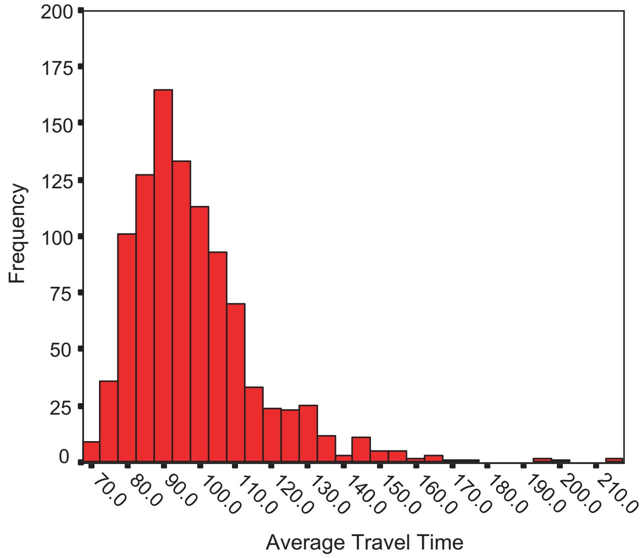

Fig. 5. Frequency distribution of average daily travel time (in vehicle-hours) for the Otley network, based on a simulation of 1000 days.

6.4. Responsive traffic signals

In this example, we apply the full model to a study of the effect of responsive signals on network performance and drivers' route choice. The model was tested on a small artificial network with four possible routes, four signalised junctions and two O–D pairs (see Fig. 6).

The signals may be set by a simple responsive *equi-saturation* policy where the green proportions allocated to each stage are determined based on the number of vehicles discharged in the previous cycle. Here, signal cycles were kept constant and a minimum green period of 8 s was maintained. In addition, a fixed plan optimised to the average traffic condition is used for comparison. A total of 100 days and two levels of variability in daily demand ($\beta_d = 0.05$ and 0.2) were simulated. The averages and standard deviations in network total travel times (in vehicle-hours) are summarised in Table 2. Day-to-day total vehicle-hours are shown in Fig. 7(a) and (b) for the low and high levels of variability respectively.

It can be seen that:

(a) Under both signal control policies, both the average and variance in vehicle-hours are higher at higher demand variability. This conforms with the results found in Sections 6.2 and 6.3.
(b) Average travel times are lower under the responsive policy than under the fixed plan.

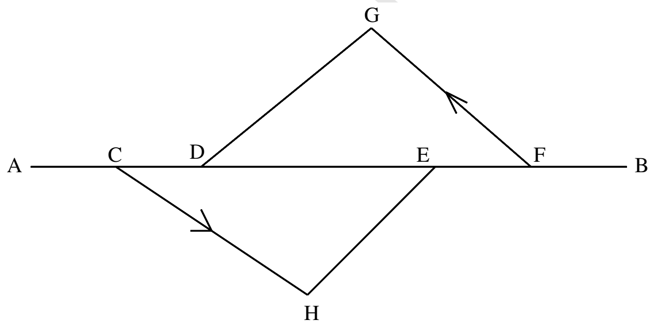

Fig. 6. The network for testing the signal control policies. Intersections C, D, E and F are signalised and the two O–D pairs are A to B and B to A. One-way streets are indicated by arrows.

Table 2
Summary results of network total travel times (in vehicle-hours) under the two signal control policies

Demand variability	Signal policy	Mean	Std. dev.
$\beta_d = 0.05$	Fixed	101.1	15.6
	Responsive	79.7	12.2
	Difference	21.4	
$\beta_d = 0.2$	Fixed	111.5	44.0
	Responsive	84.6	36.0
	Difference	26.9	

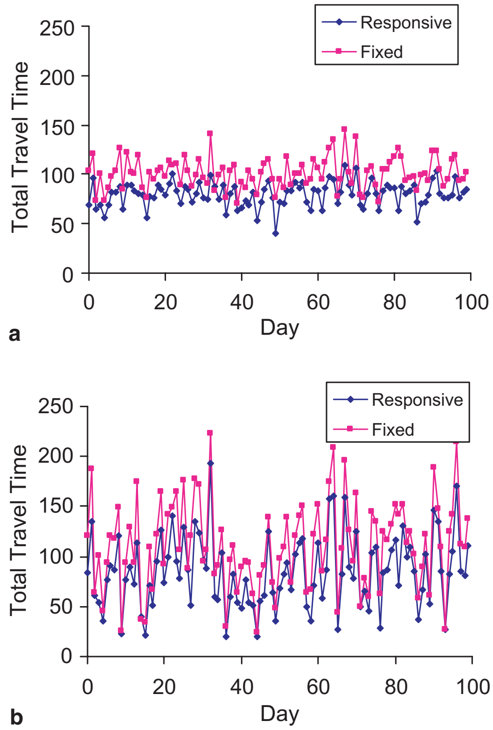

Fig. 7. Network total travel time under the fixed and the responsive signals, for demand variability of 5% (a) and 20% (b).

(c) The responsive policy performed even better over the fixed signals under higher demand variability; the average difference in travel times between the responsive signals and the fixed plans is 26.7 s with $\beta_d = 0.2$ compared with 20.4 s when $\beta_d = 0.05$ (Fig. 7).

The better travel performances produced by the responsive signals have also played an important role in drivers' route choice. Changes in signals were seen to attract drivers to the more direct routes. With the responsive plans all drivers were assigned to the two minimum distance routes by the end of 100 days, whereas with the fixed signal all four routes were used.

6.5. Scheme evaluation

In this example, we apply the full DRACULA model to a large, real-life network to examine the short-term effect of a demand-management measure on drivers' route choice and network performance. The network covers a triangular area in the north of Leeds between the outer ring road and the city centre (see Fig. 8). There are some 200 intersections, 400 links and 23,000 car trips per hour in the morning peak period. The radial routes carrying most of the traffic to the city centre in the morning are Kirkstall Road on the east, Meanwood Road on the west, and Otley Road and Spen Lane in the middle.

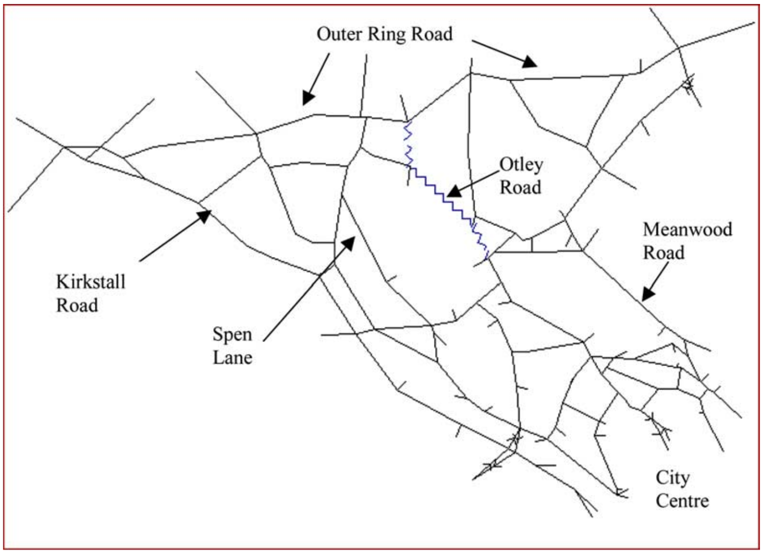

Fig. 8. The North Leeds network. The proposed bus-lanes run along the links shown as zigzag lines. One-way streets are indicated by arrows.

The proposed scheme introduces bus-only lanes on Otley Road inbound from the ring road to Shaw Lane (shown as zigzag links in Fig. 8). The road space available to general traffic is hence reduced from two lanes to one. The remaining lane is further narrowed to reduce the free-flow speed. The full DRACULA model is used to compare the route switching and travel time changes

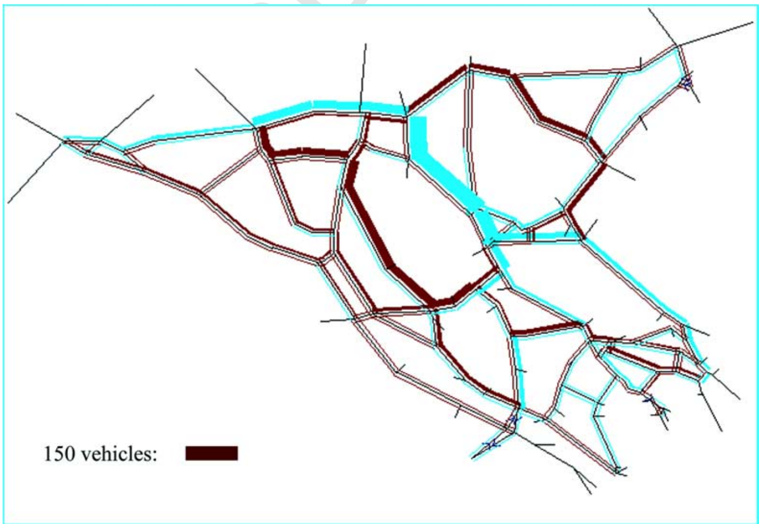

Fig. 9. Flow differences between the base and the scheme network averaged over the last 50 days. Black and grey indicate an increase and decrease of flow from the base to the scheme network respectively. The bandwidth is in proportion to the flow difference.

for the before-and-after scenarios. A total of 100 days were simulated with β_d, β_s and β_v all being set to 0.1. Only the car trips were simulated. The first 50 days the network operates without the capacity reduction on Otley Road. The bus lane was introduced on day 51 and was in operation till the end of day 100.

With the severe reduction on road capacity along Otley Road, it is expected that some route switching to alternative routes must take place. Fig. 9 shows the differences in average link flows between the 20-days before and 20-days after the introduction of the bus lane. It can be seen that flow through the upper Otley Road was significantly lower after the introduction of the bus lane, due to the reduction of road capacity on Otley Road. Much of those flows were diverted to nearby Spen Lane or Meanwood Road. An analysis of trips from the top of Otley Road just outside the Ring Road to the City Centre (an O–D pair whose minimum distance route is along Otley Road) reveals that the average journey time has increased by 10% after the scheme was introduced.

7. Conclusions

Many papers have been written highlighting the potential advantages of microsimulation approaches over traditional static equilibrium models. However, to compete with the full functionality of the equilibrium approach, especially in transport planning applications, we believe that it is essential to have an integrated approach to modelling drivers' medium-term travel decisions (choice of route and departure time, based on prior travel experiences) and the short-term evolution of traffic flow. Such an integrated approach has been described in this paper, where all decisions are treated at the microscopic level, and a consistent approach to supply and demand modelling is utilised. We have subsequently demonstrated how such an approach may be used to test complex measures and obtain forecasts that are beyond conventional equilibrium approaches, such as predictions of policy impacts on the variability in travel times and flows.

By explicitly modelling variability at several levels the approach avoids the potential bias of conventional models to over-estimate network performance as mentioned in Section 1. By working at a disaggregate microsimulation level it deals naturally with time-dependent queues which occur with junctions which are near or just over capacity. It can also deal with lane choice and lane sharing problems whereby a single vehicle at the head of a lane which is turning to the offside and is blocked by opposing traffic may therefore block that lane for straight ahead and/or nearside turns. By operating in real time it may be used to provide inputs to other real-time models such as vehicle emission and dispersion models or noise models. Since these processes do not directly affect driver behaviour they can be thought of as add-ons—albeit very important ones—rather than integral components.

While a particular collection of assumptions, which we have referred to as DRACULA, has been adopted for the purposes of the numerical experiments in this paper, the concepts and techniques apply equally to the many alternative methods of modelling microscopic traffic flow and day-to-day learning and travel choice decisions that may be found in the literature and in practice. A key element in choosing a particular collection of model assumptions will clearly be the empirical evidence in favour of those assumptions, and certainly more research is required in this area in order to test the model behaviour hypothesised in the many microsimulation approaches that have been developed. For example, although car-following theories have been around since the

1950s, it is only more recently that serious momentum has begun to test alternative theories against field data, beyond simple tests of aggregate consistency (Chakroborty and Kikuchi, 1999; Brackstone et al., 2002; Rakha and Crowther, 2003; Wu et al., 2003; Bham and Benekohal, 2004). We believe the continued study of field data to be one of the important priority areas for future research in this area.

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