

THE DRACULA DYNAMIC NETWORK MICROSIMULATION MODEL

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ABSTRACT

Recent years have seen a tremendous interest world wide in the use of microsimulation techniques to model traffic in congested road networks. This interest is particularly associated with the development of real-time, high-tech based traffic management and control strategies that react to the highly dynamic and variable nature of traffic conditions and driver behaviour. This paper introduces the DRACULA dynamic traffic network model, with the main focus on its traffic microsimulation component. The paper describes the model's theoretical and behavioural foundations, and presents illustrative examples of applying the model in the evaluation of real-time management strategies. Our experience shows that this is a particularly suitable framework for the realistic modelling of real-time technological strategies.

BACKGROUND

Transport network models have played an important role in the planning and analysis of transport policies, and in evaluating their effect on road congestion

and transport system designs. The analysis of traffic networks has traditionally been based on Wardrop's equilibrium principle, predicting a long-term average state of the network. They assume steady-state network supply and demand conditions from day-to-day and within different periods of a day, and have therefore had great difficulty in representing the dynamics of the transport systems and many of the contemporary transport policies that aim to respond to and influence travel demand and traffic conditions.

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, decrease pollution, increase road safety, etc.. 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 (e.g. Emmerink and Nijkamp, 1999); congestion management strategies, e.g. freeway ramp metering, gating (Papageorgiou et al., 1989); and responsive priority measures for public transport (e.g. Quinn, 1992; Liu et al., 1999).

A general property of all these strategies is that they both respond to – and in turn influence – actual 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 both within and between days, 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.

Recent advances in dynamic microsimulation models have produced extremely flexible frameworks whereby disaggregated, behaviour-based research can be incorporated and tested. There are generally two different approaches:

- (a) "day-to-day" models have been developed to represent dynamic adjustment of driver's daily travel choice behaviour (on route, departure time and mode), based on various behavioural principles and static or

dynamic traffic flow relationships (such as DYNASMART, Hu & Mahmassani 1997; TRANSIM, Nagel & Barrett, 1997; Emmerink et al 1994; Cantarella & Cascetta 1995; Jha et al 1999). Those proposed give great flexibility on the behavioural choice side, yet are more limited in their traffic flow modelling capabilities. Although, in some of these models, individual vehicles are represented, their movements are determined from a speed-flow relationship and based on the prevailing density on that segment of road. There is no representation of vehicles' lane-changing and car-following behaviour, making them difficult if not impossible to model complex traffic intersections, responsible signal control, bus priority measures, etc.

- (b) "pure" traffic microsimulation models have focused on individual vehicles' detailed movements and individual system elements (eg traffic lights, intersections) to represent the within-day dynamics and variability of drivers' driving behaviour. This approach has been implemented in software packages such as CORSIM (Nsour & Santiago 1994), AIMSUN2 (Barcelo et al. 1995), VISSIM (Fellendorf et al 1997), and PARAMICS (Laird et al. 1998). These models are based on car-following and lane-changing rules and have shown themselves capable of representing real-time policies. However, they either have no concept of a route, or have routes determined exogenously by an assignment model operating at a different level of traffic flow detail.

Taking the best elements of the above two approaches and setting them within a single, consistent framework, the DRACULA (Dynamic Route Assignment Combining User Learning and microsimulAtion) model was developed as a new approach to model dynamics in transport networks. At its most detailed level, the model simulates explicitly individuals' daily travel choices and the movements of individual vehicles through the network, with a day-by-day driver learning process. Thus it provides strong interactions between the demand for travel and the network supply conditions.

The concept of the DRACULA approach and its main framework are described in Liu et al (1995), and briefly summarised in Section 2. Section 3 introduces briefly the day-to-day demand model of DRACULA. The main focus of this paper is on DRACULA-MARS (Microscopic Analysis of Road Systems), the traffic microsimulation component of the DRACULA system. Section 4

describes the theoretical and behavioural foundation of the model, namely the car-following, lane changing and gap acceptance rules which combined analytical and empirical understanding of the detailed transport operation and traffic behaviour on congested urban road networks. General properties of the traffic simulation are presented in Section 5. This is followed, in Section 6, by demonstrations of the model in a study of dynamic traffic signal controls, an evaluation of Intelligent Speed Adaptation systems and in the assessment of congestion road pricing policies. The paper concludes with a summary and current and future research activities with DRACULA.

DRACULA MODEL STRUCTURE

The dynamic network microsimulation model DRACULA has been developed at University of Leeds since 1993 (Liu et al. 1995). As with conventional 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 car-following and lane-changing rules.

The demand stage predicts the level of individual demand for day k from a full population of potential drivers and the supply model for day k 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 $k+1$. The process continues for a pre-specified number of days. 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:

Day-to-day (demand) loop:

1. [Initialisation] Establish a population of potential drivers with individual characteristics and assume initial driver perceptions for each link in the network. Set day counter $k=1$.

2. [OD demand] Select the total day- k demand for each origin-destination pair according to some given probabilistic rules;
3. [Route choice] Each individual travelling on the day chooses a route based on their current perception of traffic conditions and previous experiences.
4. [Supply variability] “Global” network supply conditions are selected for day k prior to loading by some given probability laws to simulate effects such as weather and lighting conditions. For “local” variations in network conditions (such as road works, incidents occurring on the day), specify the location and duration of the incidents.

Within-day (supply) loop:

5. [Traffic loading] A microscopic simulation of traffic conditions on day k is carried out given the choices above. Drivers experience within-day variable link and turn travel times for the route they have chosen.
 - a. [Initialisation] Set within-day simulation clock $t=0$.
 - b. [Vehicle Generation] Vehicles enter the network at their origin following a shifted negative exponential headway distribution with the mean flow representing the average demand from the origin and a minimum headway of 1 second. Each vehicle is given 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 rules, lane-changing rules, gap acceptance rules and traffic regulations at intersections.
 - d. [Emission Calculation] Calculate emissions and fuel consumption for each individual vehicle according to their current driving mode: acceleration, deceleration, idling and cruising, and emission factors and relations to fuel consumption.
 - e. [Traffic Control Update] For each signalised junction, update the stage change-over clock according to desired signal plans (fixed plans or responsive). Check if the any incident is to start or to finish.
 - f. [Data Collection] Individual drivers’ experience within-day are stored. Aggregated measures such as queue length, travel time, speed, flow, emissions, fuel consumption for each link, each OD pair and the whole network are recorded.

- g. [End of day] If all drivers have finished their journey, terminate the day; otherwise increment the simulation clock and return to step 5b.
- 6. [Learning] At the end of day k , drivers update their perceptions based on their experiences on the day.
- 7. [Stopping test] If some stopping conditions is satisfied, terminate; otherwise increment the day counter and return to step 2.

Similar models of this structure have been considered previously by Ben-Akiva et al. (1986), Cantarella & Cascetta (1995), Vythoulkas (1990), Emmerink et al. (1994), and Mahmassani & Jayakrishnan (1991). The functionality of the day-to-day demand loop is briefly described in the next section. The main focus of this paper will be on the traffic microsimulation used in the within-day supply loop.

DAY-TO-DAY VARIABILITY OF DEMAND AND SUPPLY

Day-to-Day Demand

The DRACULA approach is based on the concept of a large “population” representing all the potential drivers in the study area. In practice a more pragmatic approach has been used in which we aim at generating a population whose trip making behaviour at the aggregated day-to-day level matches the averages and variances observed in real life. Existing conventional trip matrix T_{ij} from origin i to destination j has been used in all our applications to generate the population. On any particular day within the evolution of the model, any individual’s decision as to whether to travel or not is then constrained by the predicted daily trips for their particular origin-destination pair. We assume that the day-to-day variability in demand may be described by a normal distribution whose mean is T_{ij} and whose variance is $\beta_d^2 T_{ij}^2$, where $\beta_d > 0$ is a user-set coefficient of demand variation. Hence the demand for ij trips on day k is:

$$t_{ij}^{(k)} = \text{Nor}(T_{ij}, \beta_d^2 T_{ij}^2) \quad (1)$$

Route Choice

A number of route choice mechanisms have been implemented in DRACULA. The default option is the “bounded 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:

$$C_{p1} - C_{p2} > \max(\eta \times C_{p1}, \varphi) \quad (2)$$

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

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.

Learning Model

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. Such options can be added to the program if future research suggests so. 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 $N < M$.

Supply Variability

The effect of day-to-day variability of network condition is represented at two levels. The global variability represents the effects of weather, daylight etc, and is represented in the model by a variable link cruise speed through a normal distribution:

$$v_a^{(k)} = \text{Nor}(V_a, \beta_s^2 V_a^2) \quad (3)$$

where $v_a^{(k)}$ is a random variable representing the cruise speed of link a on day k , V_a the average cruise speed for the link and β_s a global coefficient of variation representing the daily variation in link speed.

Locally, incidents (such as breakdowns or road closures) 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 (through the traffic simulation described in the next section) the travel times of vehicles travelling on that day, but not on the routes individuals take.

THE TRAFFIC MICROSIMULATION

The traffic model in DRACULA is a microsimulation of the movements of (pre-specified) vehicles through the network. Drivers follow their pre-determined routes and en-route they encounter traffic 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) - a few are mentioned in Section 1. 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 network controls such as signals. Rather than adopting an existing model, in DRACULA we elected to develop our own microsimulation model from scratch because of the strong need to control the interaction between the supply and demand models and, in particular, the need to associate a specific route and destination with each vehicle.

The simulation is based on fixed time increments; the speeds and positions of

individual vehicles are updated at an increment of one second. 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 data including global and local variations and trip information (demand and routes determined by the demand model). It then runs through an interactive procedure at the pre-defined time increments, within which the following tasks are performed:

- a. Update the state of traffic signal controls, and check if any incident starts or ends;
- b. Generate new entry vehicles and place them on their entrance links;
- c. Loop through all vehicles in the network, and for each one of them:
 - i. check if the vehicle wants to change lane and, if so, whether the gaps are acceptable;
 - ii. update the vehicle's speed and acceleration and advance it to its new position. At the end of the link, either remove the vehicle from the network (if it has arrived at its destination) or pass it to its next link en route;
 - iii. calculate vehicle emissions and fuel consumption, and record traffic performance measures;
- d. Update the graphical display if required;
- e. Update the simulation clock and return to step a.

Simulation Time Periods

Three time periods were simulated in DRACULA; these are schematically depicted in Figure 1. The “demand period” is the main simulation period (time t_1 - t_2 in Fig. 1); it is typically one hour representing the peak period. In addition, a warm-up period (0 - t_1) is simulated with demand linearly increasing from half of the peak level to the peak level as a way of ensuring that the traffic from the demand period does not start with an empty network. At the end of the main period, the simulated demand linearly decreases to half of the peak level over a “cooling-off period” (t_2 - t_3) and thereafter stays at that level until the end of the simulation (t_4). The simulation ends when all vehicles departing during the demand period have completed their journey.

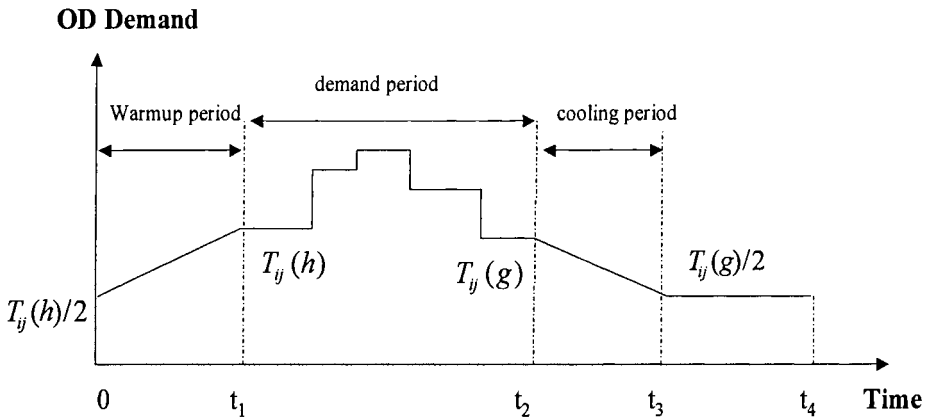


Figure 1. Time periods and the demand levels in each time period as simulated in DRACULA. $T_{ij}(h)$ and $T_{ij}(g)$ represents the O-D demand level at the beginning and end of the main period respectively. The time t_1 , t_2 , t_3 are user-defined variables, whilst the end of simulation time (t_4) is variable depending on congestion levels in networks.

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. There is no restriction on the number of roads connected to an intersection.

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. For each permitted turn, the lane(s) in the link that can use this turn are specified and a marker describing its priority over opposing flows is given.

In the model traffic moves in lanes. A lane can be reserved for a particular type(s) of vehicles, for example, a reserved bus lane. The reserved time periods and set-backs at either end of the reserved lane can be specified. Figure 2 depicts some of the network features represented in DRACULA.

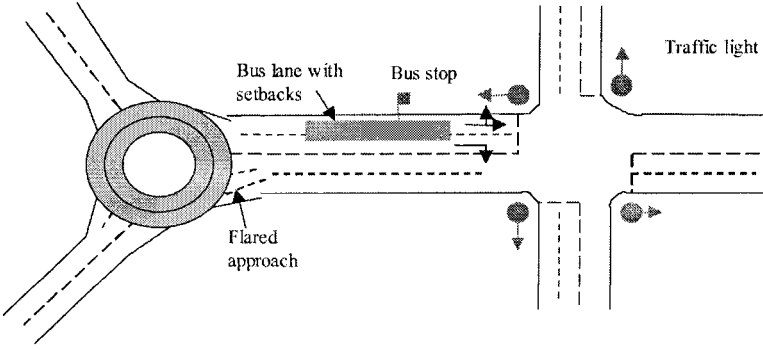


Figure 2. Network features.

Vehicle Characteristics

Vehicles are individually represented; each has a set of individual characteristics including vehicle type (e.g. car, bus, guided-bus, taxi, LGV, or HGV), vehicle length, desired minimum distance headway, normal and maximum acceleration, normal and maximum deceleration, desired speed relative to the mean speed on any individual link and acceptable gap. These characteristics are randomly sampled from normal distributions representative of that type of vehicle, subject to a lower and an upper bound:

$$p_u^n = \max \{P_u^{\min}, \min[P_u^{\max}, \text{Nor}(P_u, \beta_{pu}^2 P_u^2)]\} \quad (4)$$

where p_u^n is the value of parameter p for vehicle n of type u . P_u , P_u^{\min} and P_u^{\max} are the average, lower and upper bounds respectively of parameter p and vehicle type u , and β_{pu} the coefficient of variation for variable p and type u . The default values are based on a number of sources including May (1990) and ITE (1982).

Vehicle Movement Simulation

Vehicle movements in a network are determined by the vehicle's desired movement, its response to traffic regulations and interactions with neighbouring vehicles. The simulation maintains a linked list of vehicles in each lane and moves individual vehicles according to a car-following model and a lane-changing model, and their response to traffic controls at

intersections.

Car-Following Model

The car-following model calculates a vehicle's acceleration and speed in response to its desired speed and the relative speed and distance of the preceding vehicle. Depending on the magnitude of the relative distance, a vehicle is classified into one of three regimes: free-moving, following or close-following.

Free-moving: when a vehicle is the leading vehicle in its lane and its position relative to the stop-line of the link is larger than a pre-defined threshold d^h , or if its preceding vehicle is more than d^h further ahead, the vehicle will accelerate or decelerate freely in order to maintain its desired speed.

Following: when the space headway becomes shorter than d^h but longer than a lower threshold d^l , the vehicle will take a controlled speed which is derived from the relative speed and distance of the preceding vehicle in a manner similar to that used in NEMIS (Mauro, 1991):

$$v_n^{following}(t + \tau_n) = c_1 v_n(t) + c_2 v_{n-1}(t) + c_3 [x_{n-1}(t) - x_n(t) - L_{n-1} - s_n^{\min}] \quad (5)$$

where n and $n-1$ denote the subject and its preceding vehicle, v and x the speed and position of the vehicle. τ_n is the reaction time, s_n^{\min} the minimum safety distance of vehicle n , and L_n the length of vehicle $n-1$. Parameters c_1 , c_2 and c_3 are constants.

Close-following: when the space headway is below d^l , vehicle n will prepare to stop in case the preceding vehicle brakes suddenly. The Gipps' (1981) safety speed is used here:

$$v_n^{close}(t + \tau_n) \leq d_n \tau_n + \sqrt{d_n^2 \tau_n^2 - d_n \{2[x_{n-1}(t) - x_n(t) - L_{n-1} - s_n^{\min}] - v_n(t) \tau_n - v_{n-1}^2(t) / d'_{n-1}\}} \quad (6)$$

where d_n is the deceleration of vehicle n and d'_{n-1} the deceleration of vehicle $n-1$ perceived by vehicle n .

The actual speed of the following vehicle n is chosen as the minimum of the two speeds derived from equations (5) and (6). In all cases, drivers will not want to move at a speed exceeding their desired one, accelerate at a rate exceeding their maximum acceleration, or decelerate above their maximum deceleration rate. When a vehicle moves at a speed below a minimum speed, the vehicle is regarded as stationary.

Lane-Changing Model

The lane-changing model contains three steps: (1) obtain the lane-changing desires and define the type of changing, (2) select the target lane, and (3) change lane if gaps are acceptable.

The model divides drivers' lane-changing desires into one of five types when drivers have to or want to change lane in order to:

- (a) reach a bus stop on the link;
- (b) avoid a restricted-use lane or incident;
- (c) make their turn from the next junction;
- (d) move into a lane reserved for their type; or
- (e) gain speed by overtaking a slower moving vehicle.

The first three types are “mandatory”, i.e. the lane-changing has to be carried out by a certain position on the current link; the other two types are “discretionary”. Whether a discretionary lane-change 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 higher by a threshold.

When a vehicle wishes to change lane, it looks for a target lane. The target lane is generally determined by the lane-changing requirement, except in the case of overtaking which is only permitted from the nearside to the offside. Once it has chosen a target lane, it examines the “lead” and “lag” gaps in its target lane and makes the lane-changing movement immediately if both gaps are acceptable. For discretionary lane-changing, a gap is acceptable if it is greater than a minimum safety distance G_n^{min} which vehicle n wants to keep in case the preceding vehicle breaks suddenly:

$$G_n^{\min}(t) = v_n(t)\tau_n + v_n^2(t)/2d_n - v_{n-1}^2(t)/2d_{n-1}' + s_n^{\min} \quad (7)$$

The acceptable gap for mandatory lane-changing decreases as the vehicle gets closer to its “target point”. The target point can be a bus-stop, the position of an incident, or the end of the queue from the stopline (in the case of lane-changing for next junction turning). If a vehicle gets nearer to its target point but has not been able to change to the target lane, the vehicle may slow down and eventually stop and wait for an opportunity to change lanes. When the speed on the target lane is below a pre-defined threshold, some drivers on the target lane may deliberately slow down in order to create gaps for the subject vehicle to join. These drivers are randomly selected from a pre-defined proportion which is related to the type of subject vehicle (for example, there might be a higher proportion of people willing to give way to buses than to cars). Vehicles can only change one lane at a time. After one such manoeuvre, the vehicle has to wait for some time before making another lane-changing attempt.

Simulation outputs

The traffic simulation records the link travel times for each demand trip (those depart during the “demand period”) and passes this information to their individual knowledge base which in turn update that individual’s perception of the network. To measure the performance of a network, the simulation also provides summary statistics on link-, route- and network-wide average travel time, speed, queue length, fuel consumption and pollutant emission over regular time periods. A distinction is made in DRACULA between the “supply” costs for a given demand and the “performance” measures over a specified space-time area. This distinction is described in detail in the next sub-section.

The most detailed records are the second-by-second individual vehicles’ locations and speeds. The model also provide point- or loop-based detector measures on headway distribution, flow, occupancy and speed. For each bus service, the model summarizes the mean and standard deviation of total journey time and journey time between stops, a measure which can help distinguish service delay due to traffic congestion from that due to poor management. A graphical animation of the vehicles’ movements can also be

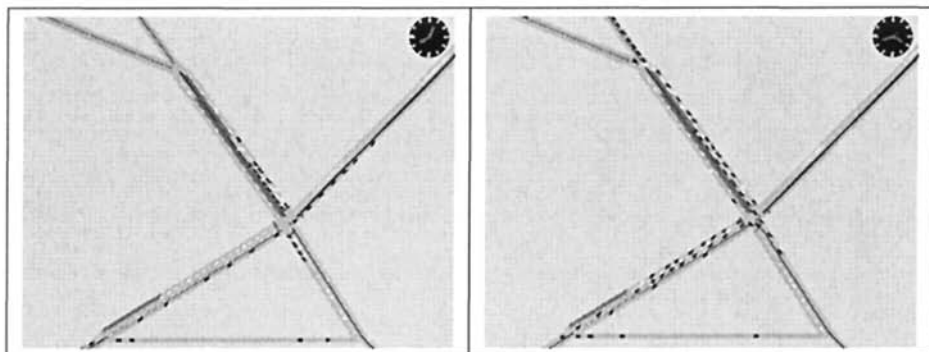


Figure 3. Simulated traffic conditions at Clifton Green intersection in the City of York. Two snapshots were taken at time 08:04 (a) and 08:20 (b) as shown by the clock on each snapshot. Vehicles are shown as coloured rectangles. Parts of the network were blocked due to roadwork, which is shown in dark grey.

shown in parallel with the simulation, giving the user a direct view of the traffic condition on the network. Fig. 3 displays two snapshots from a simulation of a signalised intersection in York; they show clearly the changes in traffic conditions between the beginning and the middle of a morning peak period.

Network performance and supply measures

DRACULA makes clear distinction between the performance of a network and costs associated with a given demand (the supply costs). The performance of a network or a single link can be measured in terms of flow performed and time performed in a defined period. They are engineering description of the performance of the link or 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 curves”).

The performance measures are based upon time-sliced approach (see Figure 4), whereby the simulation period is divided into a number of equal performance periods. The traffic flow (q), traffic density (k) and average speed (v) for link a of length L_a over time period $(h, h + \omega)$ can be calculated as:

$$q_a(h) = \frac{\sum_{n=1}^{N_a(h)} x_n(h)}{L_a \omega}, \quad k_a(h) = \frac{\sum_{n=1}^{N_a(h)} s_n(h)}{L_a \omega}, \quad v_a(h) = \frac{\sum_{n=1}^{N_a(h)} x_n(h)}{\sum_{n=1}^{N_a(h)} s_n(h)} \quad (8)$$

where $x_n(h)$ is the distance and $s_n(h)$ the time travelled by vehicle n in the space-time area $L_a \times \omega$ at the start of time h , and $N_a(h)$ the number of vehicles on link a during the period $(h, h + \omega)$.

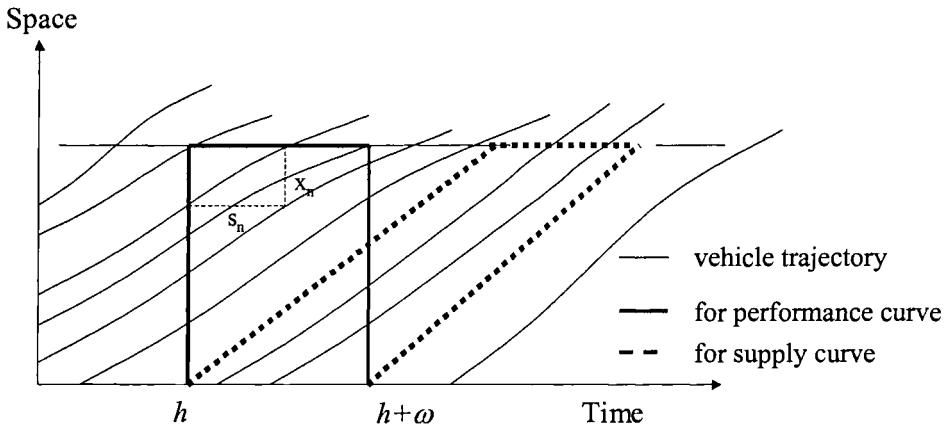


Figure 4. Space-time domains used to measure performance and supply costs.

The supply costs reflect the costs experienced by a driver using the network at a given level of demand; and they can be used to describe the way in which costs of using a network rise as demand-levels increases (the “supply curve”). 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. Thus the space-time domains used to measure performance curves and supply curves are different, as shown in Fig. 4, and supply curves cannot be readily observed in the way that performance curves can.

Supply measures track individual vehicles through the network and summarise

their trajectories over a given time period. The summation can be done with over a “departure time period” or an “arrival time period”. In DRACULA, the departure-time aggregated supply measures are recorded.

In tracking them through the network, DRACULA collects individual vehicles’ link journey time. Let us denote $y_a^n(t)$ as the journey time traversing link a by vehicle n who entered the link at time $t=(h, h+\omega)$. Then the supply cost for vehicle n travelling on link a will be:

$$C_a^n(t) = VOT^n \times y_a^n(t) + VOD^n \times L_a \quad (9)$$

where VOT^n and VOD^n are values of travel time and distance (operating costs) for vehicle n . The average generalised cost for trips departed in time period $(h, h+\omega)$ along path p from OD-pair ij will be:

$$C_{p,ij}(h) = \sum_{t=h}^{h+\omega} \sum_{n \in N_{p,ij}(t)} C_p^n(t) / \sum_{t=h}^{h+\omega} N_{p,ij}(t) \quad (10)$$

where $N_{p,ij}(t)$ is the number of individuals entering the network at time t using path p_{ij} . The supply costs for individual OD pair ij can be obtained by a trip-weighted average for all paths:

$$C_{ij}(h) = \sum_{p \in \Pi_{ij}(h)} N_{p,ij}(h) C_{p,ij}(h) / T_{ij}(h) \quad (11)$$

where $N_{p,ij}(h)$ is the number of vehicles using path p between origin i and destination j departing in period $(h, h+\omega)$, $\Pi_{ij}(h)$ the set of paths used and $T_{ij}(h)$ the number of vehicles travelling between origin i and destination j by vehicles departing in period $(h, h+\omega)$. The supply curve for the whole network is then calculated as a trip-weighted average over all O-D pairs.

MODEL PROPERTIES

Model Implementation and Performance

The program is originally written in C and later incorporated C++

object-oriented programming. The program operates under the PC Windows environment. The implementation imposes no limitation on the size of the network, nor the demand level. The processing speed does not appear to be affected significantly by the size of the network, either. It does, however, decrease as the number of vehicles travelling on the network at the any one time increases.

Figure 5 shows the simulation processing speed (measured as the ratio of the time simulated to CPU time) as a function of traffic density in a network using a Pentium II-300 PC. The network is based on the city of Leeds which covers a triangular area of the city centre and north part of the city, with some 200 intersection and 23,000 trips/hr in the morning peak period. It can be seen from the figure 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.

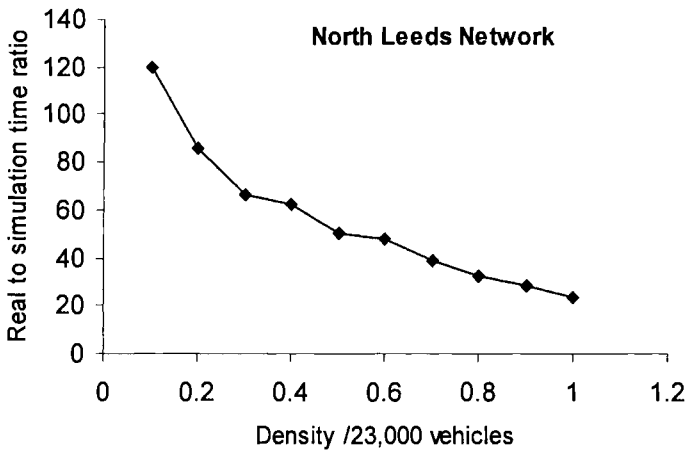


Figure 5. Simulation processing speed versus traffic density.

General Properties

Fig. 6 shows the relationship between traffic flow and density as simulated by DRACULA on a single-lane circular test track. Measurements were taken from virtual detectors located on the test track. The figure shows several distinct traffic flow regimes typically exhibit in uninterrupted traffic flow operations

(see May, 1990). The part of the curve pointed by A in Fig. 6 represents the free-flow condition, whilst the area pointed by C shows the typical characteristics of discharge traffic after a jam. The complete flow-density plot resembles the mirror image of a reversed λ , with the maximum flow of free-flow traffic (point B in Fig. 6) being considerably higher than that of the congested traffic (point B'). This is another prominent feature of traffic flow, known as "capacity drop" as first discussed in Edie (1961) and evident in other experimental data (e.g. Koshi et al, 1983).

Saturation flow is an important measure of traffic performance at signal-controlled intersections. Fig. 7 shows the discharge rates of vehicles crossing a signalised intersection versus the green time as simulated by DRACULA. The number of vehicles crossing the stop-line was recorded and averaged over one-hour simulation to produce the average discharge flow rates. Three levels of arrival flows are modelled. It can be seen that as the demand flows increase the peak of discharge rates gets more and more stable; the stable (flat) discharge rate gives the saturation flow for that approach. The example demonstrates that the traffic simulation of DRACULA has a fair representation of the travel behaviour and traffic operation at signalised intersection.

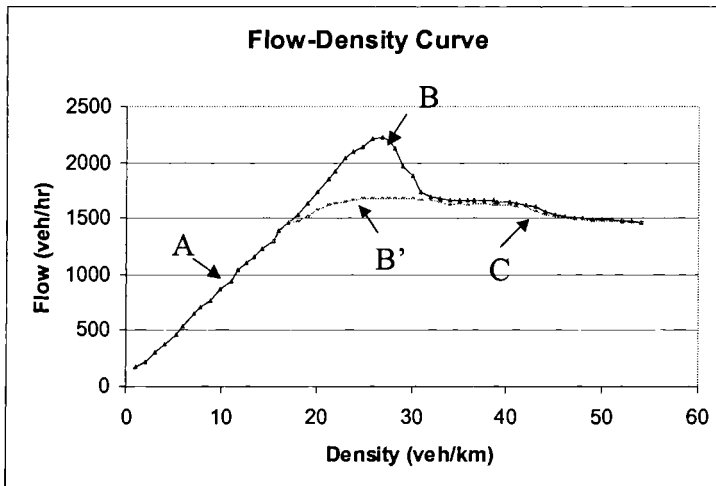


Figure 6. Simulated flow-density relationship.

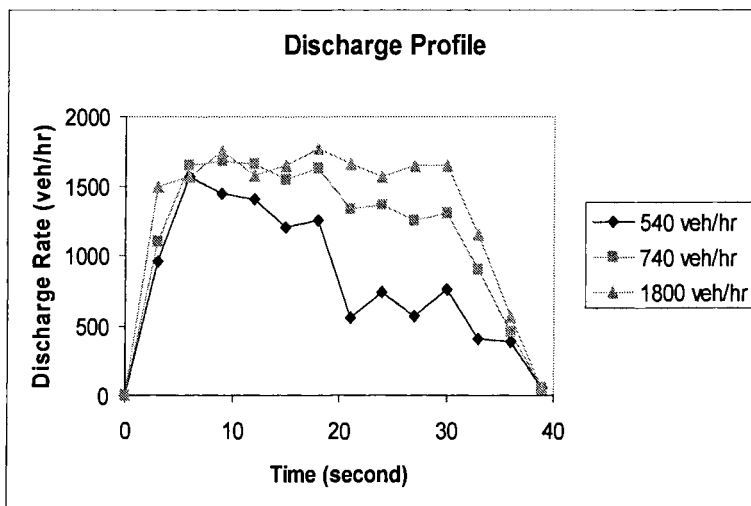


Figure 7. Discharge profiles at a signalised intersection. Time is measured from the start of green.

The trajectories of vehicles travelling along a single-lane corridor (without lane-changing) with two signalised intersections en-route are shown in Figure 8. The abscissa of the figure is the times (in seconds) and the ordinates represent the spaces travelled along the lane: each trajectory indicates the sequence of positions occupied by a vehicle in successive instants along the axis of the corridor. The figure shows a number of common features exhibited in traffic streams. First, platoons were formed either due to the lack of opportunity of overtaking (for example, as those featured around area marked as A in Fig. 8) or because of the delay by traffic lights (feature B). Second, there is significant variability in vehicle speeds (feature C) even at free-flow conditions. In general, the figure shows that the model is able to simulate responses of drivers to traffic signal control successfully.

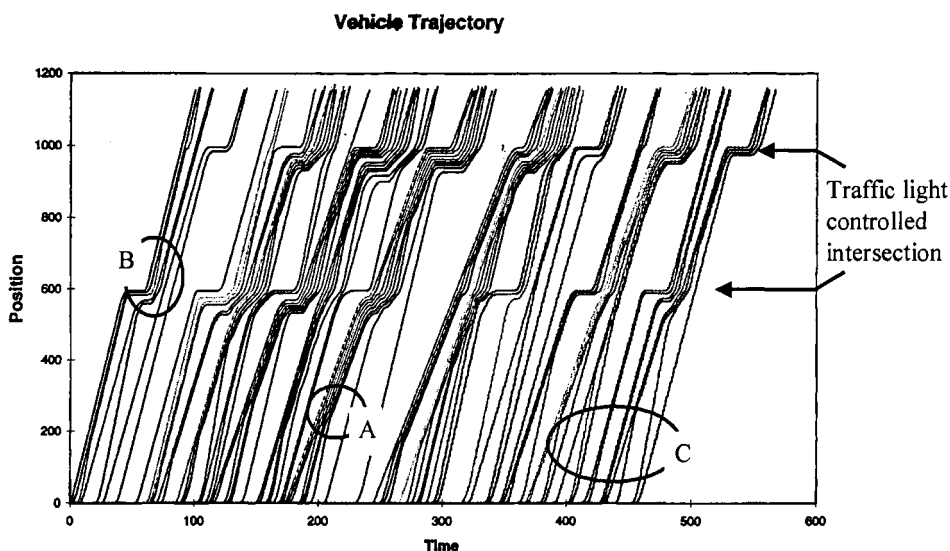


Figure 8. Trajectories of vehicles simulated along a single-lane corridor.

NOVEL APPLICATIONS

DRACULA has been developed as a flexible framework through modular implementation of its sub-models. At its most detailed level, DRACULA represents individual drivers' day-to-day choice making processes and individual vehicles' movements through a network. 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.

Similarly the demand route choice can be derived from a static equilibrium assignment, but applied to the vehicle-by-vehicle simulation. DRACULA is compatible with the equilibrium model SATURN (van Vliet, 1982) such that it can use the network and route assignment from SATURN and combine them with its detailed microsimulation to model the supply-side effect of real-time strategies. The microsimulation model requires essentially the same basic data as a macroscopic model such as SATURN - nodes, links, number of lanes per

link, lane markings, signal operations, giveaway rules, etc., with some extra data related to the geometry and size of intersections for example. Applications of the DRACULA traffic microsimulation model with route choice generated from SATURN equilibrium assignment are presented later. The flexibility of the framework ensures that, while keeping its novel aspects in one way or the other, DRACULA can be linked to a greater or a lesser extent with existing models. Current data bases will almost certainly provide the best starting points for new models.

Next we present some results from applications of DRACULA in modelling dynamic systems on drivers' route choice and system performance, and in evaluating new technology and traffic management. 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.

Responsive Traffic Signals

In this example, we apply DRACULA to a study of the effect of responsive signals on network performance and drivers' route choice. The full DRACULA model was tested on a small artificial network with 2 O-D pairs, 4 possible routes and 4 signals (see Figure 9).

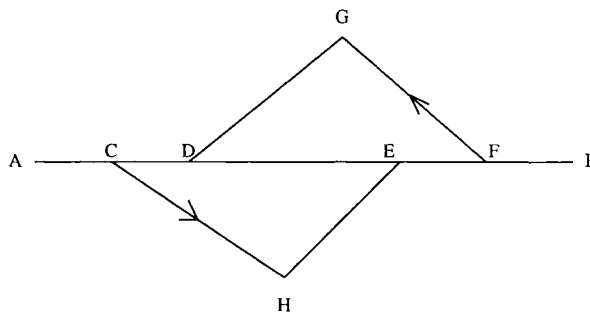
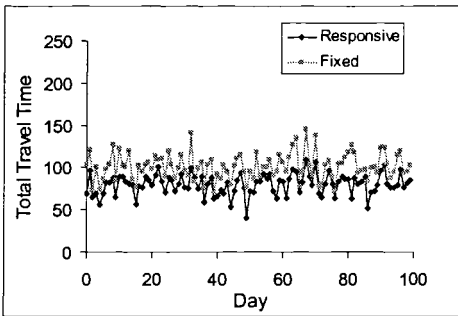


Fig. 9. The network for testing the signal control policies. Intersections C, D, E and F are signalized and the two OD pairs are A to B and B to A. One-way streets are indicated by arrows.

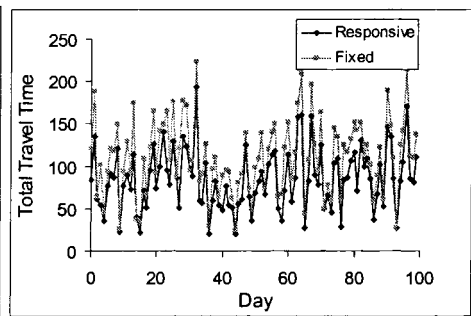
The signals may be set by a simple responsive “equi-saturation” policy where the green proportions allocated to each stage are determined based on the number of vehicles discharged in the previous cycle. Here, signal cycles were kept constant and a minimum green period of 8 seconds was maintained. In 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 summarized in Table 1. Day-to-day total vehicle-hours are shown in Figures 10 for the low and high levels of variability.

Table 1. Network total travel times (in vehicles-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	



(a)



(b)

Fig. 10. Network total travel time under the fixed and the responsive signals for demand variability of 5% (a) and 20% (b).

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;
- (b) Average travel times are lower under the responsive policy than under the fixed plan; and
- (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 26.7sec with $\beta_d=0.2$ compared with 20.4sec when $\beta_d=0.05$ (Fig. 10).

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.

Intelligent Speed Adaptation (ISA)

ISA systems use in-vehicle electronic devices to control the maximum speeds of vehicles to the prevailing speed limits through, for example, communication with a Global Positioning System. The main advantage of ISA systems relative to other forms of urban speed control measures (such as 20 mph zones or traffic calming measures) is its flexibility. The system allows for different control speed limits to be set up for different time of day, and under different traffic, roadway and weather conditions. They are increasingly appreciated as a flexible method for speed management and control, particularly in built-up areas. Large-scale on-road trials of the systems are being carried out both in the mainland Europe and in the UK (e.g. Almquist et al., 1991; Lind, 1999)

An urban traffic network in the east of Leeds was set up to simulate the effect of ISA. The network covers two radial routes from the outer ring road to the city centre, stretching over some 15km (Fig. 11). There are 240 links connecting 120 intersections. Two levels of speed limits were set according to road type: a 40mph speed limit is set for the two radial routes and a 30 mph limit for all residential streets. In addition, on one of the entry links on the ring road, a national speed limit of 70mph was defined. Figure 11 shows the speed limit distribution over the network. A morning peak network (with some 18,000 car-trips per hour) and an off-peak network (with some 12,000 trips/hour) were set up in order to examine the performance of ISA under

different traffic congestion levels. The base networks were calibrated against observed link counts and floating-car journey times (Liu & Tate 2000).

The ISA penetration rate was introduced as a control variable in DRACULA. Simulations for both the morning and off-peak periods were carried out with 10 ISA penetration rates: 10, 20,...,100% of the total fleet were equipped with ISA. The results were compared with the base case where there was no ISA speed control. For each scenario, the model was run 10 times with different random number seeds to establish a distribution of the results.

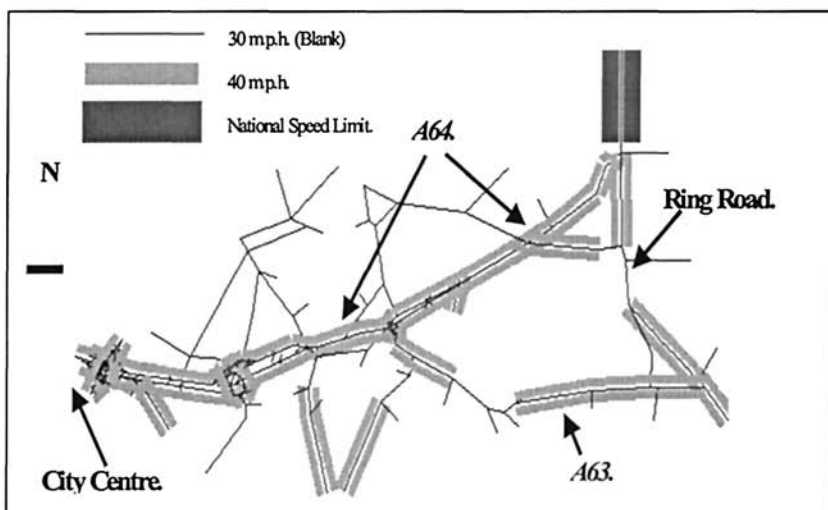


Figure 11. Distributions of ISA speed limit in the East Leeds network.

Figure 12 shows the speed distributions over the full range of ISA penetrations simulated for the two time periods. The x-axis shows the speeds (in 5 km/hr bands), and the y-axis the total vehicle-hours spent in each speed band. Each row of data represents one ISA penetration rate as a percentage. The results clearly demonstrate that the proportion of vehicles exceeding the speed limits (30 and 40 mph) decreases with increasing levels of ISA penetration. In the off-peak scenario, calculations established that in the no-control case there were 34% of vehicles exceeding the 30 mph speed limit. This was zero under full ISA control. Due to more congestion this figure is reduced to 20% during the peak period. Similarly, the level of vehicle-hours exceeding the 40 mph speed limit was 16% and 12% for the off-peak and peak periods respectively. Another feature worth noting, is that, in the morning peak period, there was a

substantially high proportion of vehicle-hours spent at speed below 10 km/hr. ISA implementation did not alter the proportion of such congested traffic by any significant amount. This suggests that, whilst ISA is effective in reducing excessive speeds, it does not induce further congestion to the network, a feature which may make such system more acceptable to the general public and the network managers.

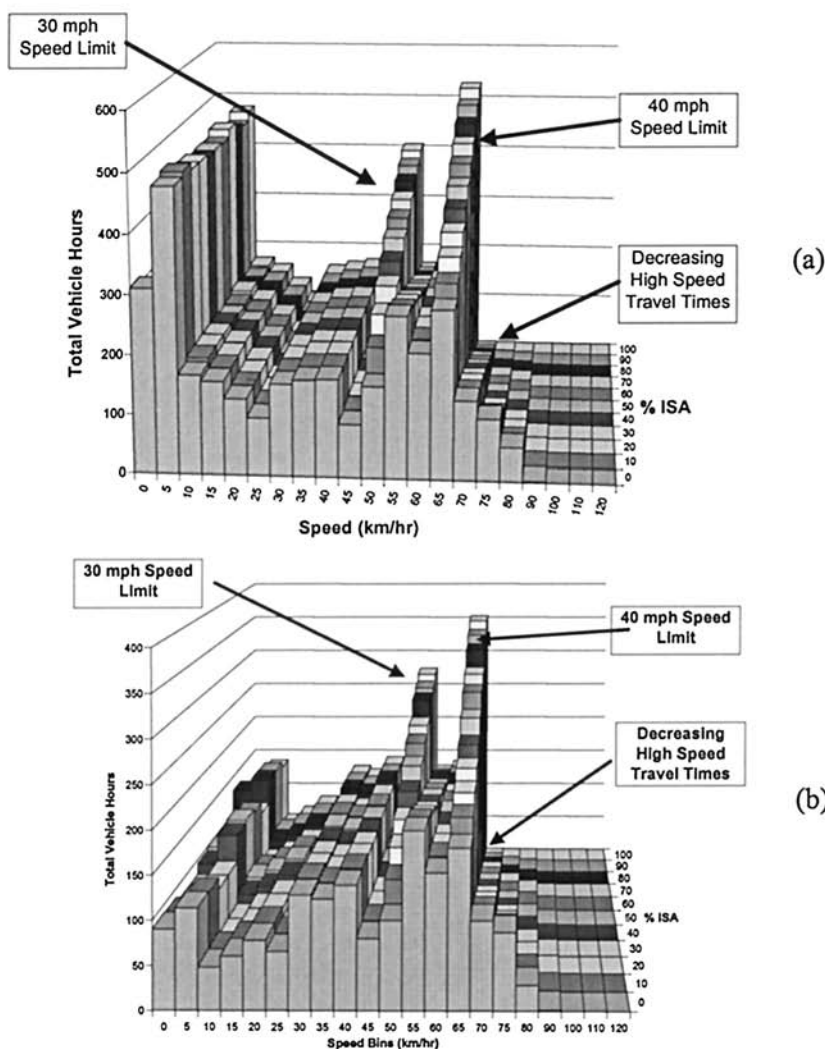


Figure 12. Speed distributions of ISA for the morning peak (a) and the off-peak period (b).

Congestion Road Pricing

This section presents an application of DRACULA in investigating the variability of *congestion metering (CM)* charges in continuous time and space, as would be experienced by individual drivers. *CM* is a congestion-based road pricing system first proposed by Oldridge (1990). The underlying concept of the *CM* system is that charges would only be levied when delays occur. This can be achieved with advanced technology on-board a vehicle through an electronic in-vehicle unit (IVU) which debits value from an inserted smartcard only when a certain, pre-specified level of delay is encountered. Linking a clock and an odometer, in similar fashion to a taxi meter, allows the IVU to perform continuous calculations of the time taken to travel a certain unit of distance. By specifying a critical time value, it is then possible to set a *congestion threshold*, above which a charge would be levied. This threshold approach has many interesting features, in particular:

- (a) charges would be expected to vary by route rather than by link;
- (b) charges may vary significantly over a relatively short timescale, related to quite small variations in network conditions close to the threshold level;
- (c) the definition of the threshold would need to include a margin of error, charging for less than 100% of delayed time, to ensure that vehicles would not be penalised for being courteous and obeying traffic regulations in un-congested conditions; and
- (d) there may be significant variations in charges on a day-to-day basis.

Previous modelling work to investigate the route and demand choice aspects of a range of charging technologies in a static modelling context has been forced to rely on a much coarser specification (May and Milne, 2000). In addition, for *CM*, often the point at which a charge occurs may not be the same point at which the delay that triggers the charge happens (as demonstrated in Fig. 14). This raises the question of how to model drivers' reactions to the road charge in terms of their perception of the network. For this reason, only a route-based, individual vehicle second-by-second simulation model can fully represent the technology envisaged for time-dependent road charging systems. DRACULA simulation is novel in that it tracks vehicles along pre-specified routes to their destination, rather than using junction-by-junction turning percentages, and is thus able to monitor the experience of individual drivers following fixed routes

to assess variations in charges between drivers and under different level of congestion and charging scenarios.

Implementing *CM* in DRACULA has required modification of the model to include four additional user specified parameters:

- (i) a charging band, representing the unit of distance over which charges are levied;
- (ii) a charging segment, representing the frequency at which charging information is assessed in distance terms;
- (iii) a charging threshold, representing the travel time allowed for the coverage of the charging segment before any charge is levied; and
- (iv) a charging rate, representing the level of charge levied once the threshold has been exceeded.

The initial values of these parameters were assumed to be 500 metres, 10 metres, 3 minutes and 30 pence per minutes respectively. Thus, for each individual vehicle on the network, it is assumed that an IVU is fitted which assesses the state of the threshold every 10 metres travelled. At that point, it reviews the travel time taken for the previous 500 metres. If time is less than or equal to 3 minutes, the vehicle is uncharged. If time exceeds 3 minutes, the vehicle is charged at a rate of 30 pence per minute for the excess time. Once a charge has been levied the state of the threshold is not assessed again until a further 500 metres has been covered. Values for the first three parameters were taken directly from those suggested in Cambridge. The unit rate of charge was chosen based on optimum levels identified in previous work (Milne 1997).

The DRACULA simulation of *CM* system has been applied to a real-world urban network of Leeds. The network has 175 nodes, 70 zones and 1748 routes used by a peak-hour demand of 23,000 trips, which is about 25% of the total morning peak demand for the city of Leeds.

Figure 13 shows the variability of *CM* charges and travel time along one of the three major radial route inbound to the city centre. It plots, for each individual vehicles travelled along the route, the *CM* charges and the effective time-based charges incurred by individual vehicles against their departure time. It can be seen that the charges levied by both charging systems, and more significantly by the *CM*, can be extremely volatile over very short periods of time and that,

therefore, drivers would have extreme difficulty in predicting the costs of their journey both within and between days, even if they were aware of the likely overall traffic levels on any given day.

Figure 14 shows link-based simulation summary statistics. It plots, in bandwidth, the delays to each link and the amount of charges levied on each link. It can be seen that the location of charges may not necessarily be the same as where delay occurred. In fact, distribution of charges is more spread spatially than delays. This difference is in part due to the way these two measures are estimated. Link delay is simply the difference between free-flow travel time and actual travel time on the link. Whilst the *CM* charges are levied by looking back a specific length (500 metres in this case) and checking the time threshold. If, for example, a congestion occurred 150m upstream of an intersection, a charge could be levied on the downstream link.

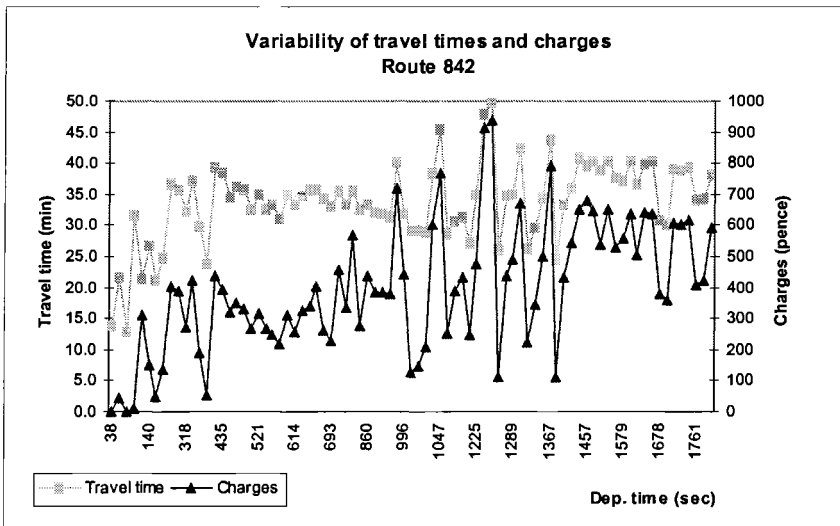


Figure 13. Variability of travel time and CM charges along a major corridor in North Leeds.

The results suggest that a practical threshold-based *CM* system may levy charges which are extremely variable over time and, thus, very difficult to predict with any accuracy by both the drivers and system managers and that the location where a charge is levied differs from the location where actual delay occurred. The results obtained suggest some potentially important implications

for the suitability of congestion-dependent charging mechanism, both for approximating the marginal costs of road travel and for providing useful incentives to drivers towards more efficient travel behaviour.

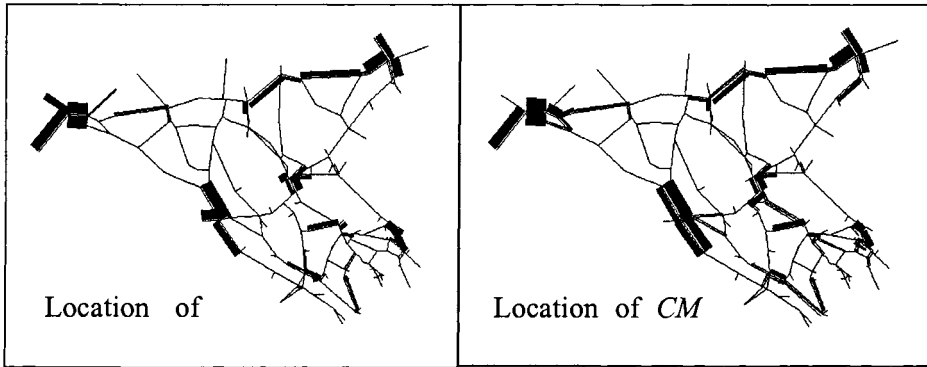


Figure 14. Spatial distribution of link delays and congestion charges levied.

CONCLUSIONS

Microsimulation method is becoming increasingly popular as a flexible approach to model the dynamics in transport systems. This paper describes a new approach to modelling road traffic assignment, code-named DRACULA, in which the emphasis is on the microsimulation of individual trip makers and individual vehicles. It represents directly driver choices as they evolve from day to day combined with a detailed within-day traffic microsimulation. It therefore models both day-to-day and within-day variability in both demand and supply. As such we believe it is a particular suitable framework for the realistic modelling of “real-time” traffic management and control strategies.

The traffic microsimulation component of the DRACULA suite is similar to many other traffic microsimulation models in that it models individual vehicles' movements based on car-following, lane-changing and gap-acceptance rules. However, it differs significantly in that it tracks vehicles along pre-specified routes from origin to their destination, rather than junction-by-junction turning percentages. The latter can lead to implausible, cyclic routes. Most of the other microscopic traffic simulators – some of them are mentioned in Section 1 – perform over a fixed time period and hence can

only provide measures on network performance. By tracking all vehicles departing from a particular time period to their destination, DRACULA is able to monitor the experiences of individual drivers to assess variations in the costs of travel between drivers, and through its day-to-day demand model, to model individuals' choices of travel based on their individual experience rather than some aggregated system measures.

The framework is undergoing further research and development, reflecting on-going research in developing real-time strategies and in the dynamic evolution of traffic networks. A model of public transport operations has been developed which allows public transport priority measures such as guided bus to be evaluated (Liu et al. 1999). Further research is underway to combine a public transport assignment model with microsimulation of bus passengers and to study the effect of passenger demand and bus scheduling on service reliability. A pedestrian microsimulation model has been developed and embedded under the general framework of DRACULA. The model simulates explicitly the complex interactions between vehicular traffic and pedestrians at signalised intersections and real-time traffic signal control strategies aimed to maximize the capacity while giving pedestrian priority (Liu et al. 2002). Research is under way to explore artificial intelligent methods, in particular multi-agent approach, to model the complex decision-making processes of drivers (Rossetti et al. 2002) and information provision and processing. It is also planned to connect the simulation model to a real-time signal control system and to incorporate dynamic en route diversion into the framework.

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