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2 Microsimulation models incorporating both demand 3 and supply dynamics

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8 Abstract

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

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

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28 the introduction of bus-only lanes in a sub-network of Leeds. Our experience demonstrates that this mod-
29 elling framework is computationally feasible as a method for providing a fully internally consistent, micro-
30 scopic, dynamic assignment, incorporating both within- and between-day demand and supply dynamics.
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32 *Keywords:* Microsimulation; Network; Route choice; Variability; Real-time strategies

34 1. Introduction

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

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

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

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

67 A large number of traffic microsimulation models have been developed in order to study
68 operational and design problems in road transport systems. Notable among the applications

69 are studies of: *automated highway systems*, such as lane routing (Eskafi et al., 1995; Lee and Lee,
70 1997), merging control (Ran et al., 1999; Hidas, 2002), ramp-metering (Hasan et al., 2002) and the
71 integrated control of access, lanes and routes (Ben-Akiva et al., 2003); *automatic vehicle control*
72 *systems* (Chang and Lai, 1997) such as adaptive cruise control (Marsden et al., 2001; Suzuki
73 and Nakatsuji, 2003) and intelligent speed adaptation (Liu and Tate, 2004); *traffic management*
74 *measures*, ranging from bus priority schemes (Quinn, 1992; Liu et al., 1999) to tollbooth design
75 (Huang and Huang, 2002), pedestrian facility design (Liu et al., submitted for publication) and
76 responsive traffic signal systems (Kosonen, 2003; Niittymäki and Turunen, 2003; Bullock et al.,
77 2004); *Incident Management Systems* including incident recognition (Mussa et al., 1998), incident
78 detection (Khan and Ritchie, 1998; Sheu, 2004), and incident response strategies (Sheu and Ritchie,
79 2001; Cova and Johnson, 2003); *real-time driver information systems* (Hu and Mahmassani,
80 1997; Dia, 2002; Adler et al., 2005; Rossetti and Liu, 2005); *traffic flow stability analysis* (Cha-
81 kroborty and Kikuchi, 1999; Huijberts, 2002; Davis, 2003; Bham and Benekohal, 2004); and
82 the *prediction of environmental impacts*, including exhaust emissions (Yu, 1998), energy consump-
83 tion (Ambrosino et al., 1999), and safety (Köll et al., 2004).

84 It is noticeable that a great majority of these applications have focused on problems of a short-
85 term forecasting nature, where microsimulation is able clearly to demonstrate its advantages over
86 static, macroscopic approaches in estimating the *immediate* traffic flow impacts of some measure.
87 However, in the present paper we are particularly interested in the potential for microsimulation
88 as a medium-term transport planning tool. In this latter case, it is crucial to consider the *secondary*
89 effects¹ caused by drivers changing their travel decisions on subsequent trips in response to their
90 new experiences of traffic conditions. Thus, for example, the implementation of a new responsive
91 traffic signal system at an intersection may lead to reduced delays in the short term, but in time
92 (over a period of days and weeks) this may lead to traffic diverting from alternative routes or
93 changing their time of trip departure, leading to a medium-term change in the magnitude and pro-
94 file of the flows that impinge on that intersection. In spite of all the criticisms of the static equi-
95 librium paradigm, it is the ability of such an approach to deal with both the immediate and
96 secondary effects that has led to its popular use in transport planning. If microsimulation is also
97 to take its place as a mainstream approach to transport planning, it must be able to address such
98 secondary effects.

99 How have microsimulation approaches been used to address these secondary effects? Three
100 main approaches may be identified. In the *first approach*, the secondary effects are neglected
101 (e.g. Laird et al., 1999). This might lead one to conclude that, therefore, no secondary effects will
102 occur in the model, but this may not be quite true. In particular, if the microsimulation input data
103 requires turn probabilities to be input at each intersection (rather than, say, complete routes to be
104 defined), then ‘routes’ are implicitly reconstructed by making Monte Carlo draws for each vehicle
105 according to these turn probabilities. If some control measure is then applied which affects the
106 sequencing of vehicle arrivals, then there will be an impact on the sampled turn *proportions*
107 due to the effective change in sequence of the random numbers generated. Thus, even though
108 no behavioural model is supplied to represent the secondary effect, an apparent effect may occur
109 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.

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

113 In the *second approach*, the secondary effects are predicted by using a coarser model which is
114 either run once in stand-alone mode prior to the microsimulation (for example, Montero et al.,
115 2001, propose the use of a static equilibrium model, with the equilibrium turning fractions then
116 input as turn probabilities to the microsimulation), or is based on some aggregated feedback loop
117 from the microsimulation (Fellendorf and Vortisch, 2000; Barceló and Casas, 2004). In neither
118 case are the secondary-level decisions made on the basis of consistent assumptions and aggrega-
119 tion levels with the microsimulation, and so one is open to the same criticisms levelled at the static
120 equilibrium approaches.

121 The *third approach* is to use some consistent mechanism to feedback the travel experiences at
122 the microscopic level and simulate individual trip choices (Liu et al., 1995; Nagel and Barrett,
123 1997; Hu and Mahmassani, 1997). In this approach, then, one effectively defines a dynamic pro-
124 cess that explains drivers' day-to-day learning and trip-to-trip travel choice adjustments. A further
125 advantage of this approach is that one can avoid the problems of turn-probability based defini-
126 tions (noted above), by requiring the day-specific inputs to the microsimulation to be *complete*
127 *paths* traversed at particular departure times, the paths and departure times both being selected
128 by the dynamic process model explaining the day-to-day adjustments. The price paid for such
129 an approach is, however, a much more complex model to interpret, with complex issues of con-
130 vergence, stability and even existence of attractive states to handle.

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

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

148 2. DRACULA model structure

149 As with conventional equilibrium models the DRACULA approach begins with the concept of
150 demand and supply (or performance) sub-models that interact with each other. However, by con-

151 trast with conventional models, in DRACULA both the demand and supply sub-models are
152 based on microsimulation and both evolve from day-to-day. In DRACULA, trip makers are indi-
153 vidually represented and their daily route choices (demand) are made based on their past experi-
154 ence and their perceived knowledge of the network conditions. Individual vehicles are then moved
155 through the network (supply) following their chosen routes according to rules governing car-fol-
156 lowing, lane-changing and intersection control. The demand stage predicts the level of individual
157 demand for day n from a full population of potential drivers and the supply model for day n deter-
158 mines the resulting travel conditions. The costs experienced by drivers are then re-entered into
159 their individual *knowledge bases* which in turn affect the demand model for day $n + 1$. The process
160 continues for a pre-specified number of days. The overall structure of the framework and the
161 interaction among its various sub-models are illustrated in Fig. 1.

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

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

169 Day-to-day (demand) loop:

- 170
171 3. [Initialisation—Part I] Set initial driver perceptions for each link in the network. Set day
counter $k = 1$.
173 4. [Daily demand] Select the total day- k demand for each origin–destination pair according to
some given probabilistic rules.
175 5. [Departure time choice] Individuals travelling on the day adjust their departure time to travel
based on previous experience.
177 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.
181 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.

185 Within-day (supply) loop:

- 186
187 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 $t = 0$.

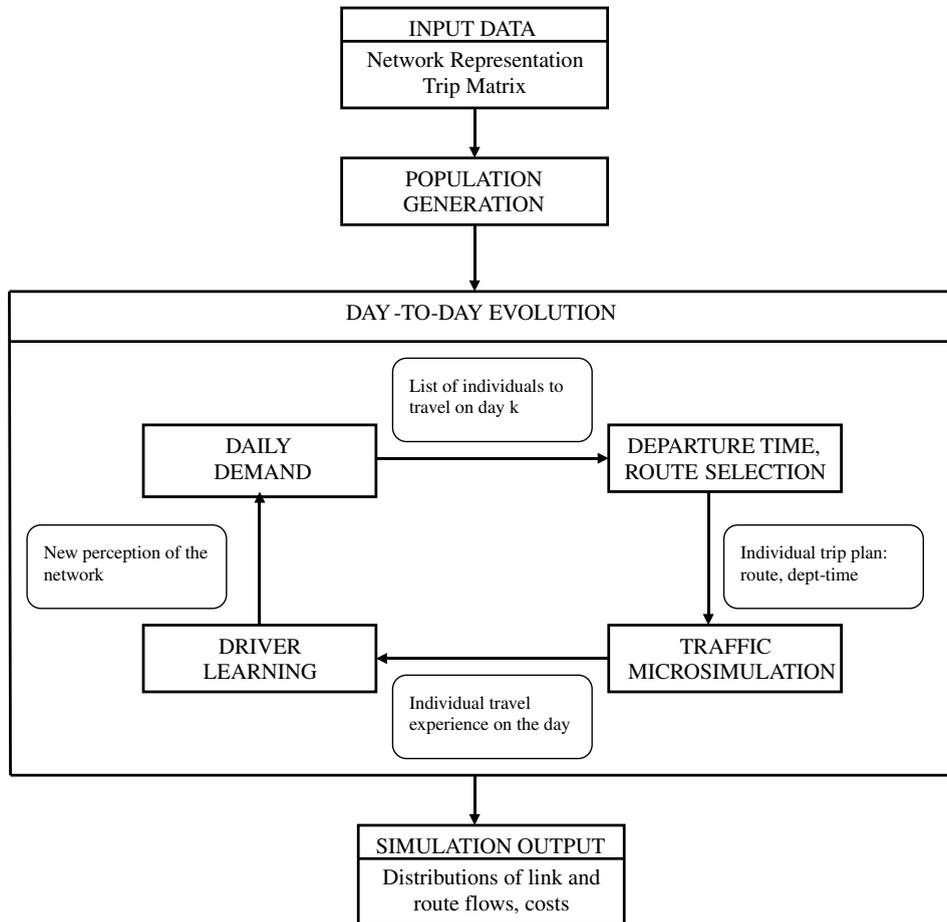


Fig. 1. DRACULA model structure.

- (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.

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

209
 210 Note that this process will not converge to a single equilibrium point but will continue to vary
 211 from one day to the next. Instead, our objective is to determine the probability distribution of
 212 individual day-to-day states, appealing to the theory of stochastic processes (Cascetta, 1989; Can-
 213 tarella and Cascetta, 1995; Watling, 1996; Hazelton and Watling, in press).

214 Similar models of this day-to-day structure have been considered previously by Alfa and Minh
 215 (1979), Ben-Akiva et al. (1986), Vythoukias (1990), Emmerink et al. (1994), Nagel and Barrett
 216 (1997), Hu and Mahmassani (1997), though generally with the day-to-day evolution represented
 217 as a deterministic process, with the aim to converge to a fixed point.

218 Details of the functionality of steps 2–7 and step 9 are discussed in Section 3. Section 4 intro-
 219 duces the traffic microsimulation model used in step 8.

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

221 3.1. Modelled population

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

229 In practice, however, simplifications and compromises will need to be made. More pragmati-
 230 cally therefore we aim at generating a population whose trip making behaviour at the aggregate
 231 day-to-day level matches the averages and variances observed in real life. In our applications, the
 232 population is derived from an existing conventional trip matrix T_{ij} from origin i to destination j .
 233 We then assume (see also Section 3.2 below) that the day-to-day variability in the number of trips
 234 may be described by a normal distribution whose mean is T_{ij} and whose variance is $\beta_d^2 T_{ij}^2$ where
 235 $\beta_d > 0$ is a user-set coefficient of demand variation. Hence the demand for ij trips on day k is:

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

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

$$T_{ij}^{\max} = T_{ij} + 3\beta_d T_{ij} \quad (2)$$

243 By default, each driver's choice on the first day of travel is based on average free-flow travel times,
 244 and for each link and turn the perception is unchanged until that link or turn is used by the indi-
 245 vidual. However the initial choices may also be specified to be those resulting from a previous

246 model run. The most obvious application of this is in a before-and-after study of a scheme, in
247 which the initialisation of the ‘after’ run is based on the final conditions of the ‘before’ run. Sim-
248 ilarly, the initial *histories* of drivers—i.e. their remembered experiences on the network—may be
249 set to be their accumulated experiences in the previous run.

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

253 3.2. Day-to-day demand

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

260 Thus for each origin i and destination j we:

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

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

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

272 3.3. Departure time distribution

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

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

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

288
 289 For example, a_{ijm} could be randomly drawn at the start of the simulation from a specified time
 290 profile as in the first method.

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

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

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

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

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

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

306 Otherwise,

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

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

312 3.4. Route choice

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

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

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

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

331 These rules are only intended as an example of the range of rules that could possibly be imple-
332 mented in a flexible approach such as DRACULA. Alternative behavioural rules that could be
333 provided in the future include the concept of risk minimization, with drivers perceiving cost vari-
334 ances as well as means.

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

338 3.5. Learning

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

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

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

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

352 3.6. Supply variability

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

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

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

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

366 4. The traffic simulation

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

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

382 4.1. Network representation

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

394 4.2. Vehicle generation

395 Vehicles are individually characterised, including a technical description of the vehicle (vehicle
396 type, length, maximum acceleration and deceleration capability) and behaviour of the driver
397 (reaction time, stopping distance headway, acceptable time gap, desired speed, desired accelera-
398 tion and deceleration). These characteristics are randomly sampled from truncated normal distri-
399 butions representative of that type of vehicle:

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

402 where p_u is a random variable representing vehicle parameter p for vehicle type u . P_u , P_u^{\min} and
403 P_u^{\max} are the mean, lower and upper bounds of the distribution respectively. β_v is the user-defined

404 coefficient of variation of vehicle characteristics which can be made vehicle-type specific. For
405 example, there may be greater variability in car drivers' desired speed and acceptable gap than
406 those of drivers of large goods vehicles. The characteristics for each vehicle are chosen at the start
407 of a simulation run and they remain the same for the same vehicle from one day to the other. Pub-
408 lic transport vehicles are represented with additional information such as service number, service
409 frequency, bus stops *en-route* and passenger demand (Liu et al., 1999).

410 The default values (as used in the numerical results reported in Sections 6.3–6.5) are based on a
411 number of sources including May (1990), Institute of Transportation Engineers (1982), Gipps
412 (1981). A discussion on the choice of parameter values for microsimulation models and their
413 impact on model results is presented in Bonsall et al. (in press).

414 4.3. Vehicle movement

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

420 4.3.1. Car-following model

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

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

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

435 4.3.2. Lane-changing model

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

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

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

445
446 The first three types are *mandatory*, i.e. the lane-changing has to be carried out by a certain
447 position on the current link, for example the location of the bus stop. The other types are
448 *discretionary*; whether such a discretionary lane-changing can be carried out depends on the
449 actual traffic conditions. For example, a vehicle would only change lane to gain speed if the speed
450 offered by the adjacent lane is *significantly* higher than that on their current lane. The threshold is
451 a behavioural variable that can be calibrated to the observed local behaviour.

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

458 4.3.3. Intersection simulation

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

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

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

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

480 4.4. Simulation outputs

481 To measure the performance of a network, the simulation provides summary statistics on the
482 link-, OD- and network-wide averages and variances in travel time, speed, queue length, fuel
483 consumption and pollutant emission, over regular time periods. The most detailed records are

484 the second-by-second individual vehicles' locations and speeds. The model also provides point- or
485 loop-based detector measures on headway distribution, flow, occupancy and speed. For each bus
486 service, the model summarises the means and variances of total journey time and journey time
487 between stops; these measures can help distinguish service delays due to traffic congestion from
488 those due to poor management. A graphical animation of the vehicles' movements can also be
489 shown in parallel with the simulation, giving the user a direct view of the traffic conditions on
490 the network.

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

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

509 5. Implementation

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

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

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

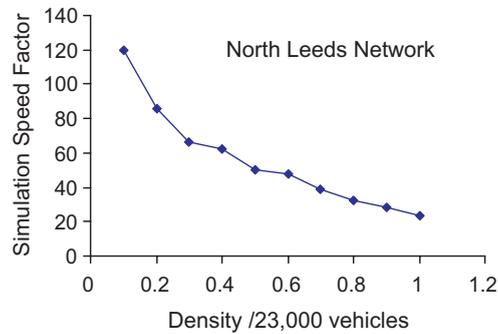


Fig. 2. Simulation speed factor versus traffic density.

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

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

535 The computer implementation of the model framework imposes no limitation on the size of the
 536 network or the demand level. The processing speed does not appear to be affected significantly by
 537 the size of a network, but decreases with the number of vehicles in the network increases. The pro-
 538 cessing speed improves significantly if the graphical animation of the simulation is switched off.
 539 Fig. 2 illustrates the simulation processing speed (measured as the ratio of the time simulated
 540 to CPU time), without animation, as a function of traffic density in a network using a Pentium
 541 II-300 PC. The network is the north Leeds network described in Section 6.5. It can be seen that
 542 the processing speed decreases exponentially as flow density increases. Even at the full demand
 543 (23,000 vehicles/hour) the simulation ran 20 times faster than real time. This shows therefore that
 544 this modelling framework is computationally feasible as a method for providing a fully internally
 545 consistent, microscopic model of both demand and supply dynamics.

546 6. Applications

547 6.1. General

548 While in theory DRACULA could be applied to studies of long term and large scale network
 549 changes, such as the construction of new motorways or a bypass, this is an area where conven-
 550 tional aggregate equilibrium models are likely to be satisfactory (although the difficult question
 551 of demand responses such as departure time changes arises even here). However the behaviourally

552 sounder microscopic models could be used to test certain key assumptions of macroscopic models,
553 and to suggest alternative methods (possibly empirical modifications) which might improve con-
554 ventional techniques.

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

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

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

570
571 Finally, it offers an opportunity to measure variability within a modelling framework. Variabil-
572 ity in journey time reliability is an issue which is probably felt to be crucial by most commuters
573 but generally disregarded by most models.

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

579 6.2. Day-to-day variability (simplified model)

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

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

589 Preliminary tests with the above model have been performed on a number of networks, ranging
590 from small artificial ones to a real-life network containing some 440 links and 20,000 individual
591 trips on average per day. Because neither the method of generating the variability, nor the actual
592 levels of variability assumed, were calibrated from real-life data, the work was considered to be

593 more of a sensitivity analysis. For this reason, it is not appropriate to report absolute figures. In-
594 stead, the general themes arising from the tests are reported. These will serve as hypotheses, to be
595 tested in the next sub-section on different scenarios.

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

604 The general findings were:

- 605 (a) As might be expected, link flow variances generally increased with a decrease in the behav-
ioural 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.
- 610 (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 ($3 \leq N \leq 10$) this instability was not evident. The mean flows
did not vary greatly with N in this latter range.
- 614 (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 $3 \leq N \leq 10$, these mean flows were
found to be well-approximated by a deterministic equilibrium model applied to the average
OD matrix.
- 618 (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.
- 621 (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).

624

625 6.3. Day-to-day variability (full model)

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

632 Fig. 3 shows the day-to-day total vehicle travel times (in vehicle-hours) over the 100 days sim-
633 ulated 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

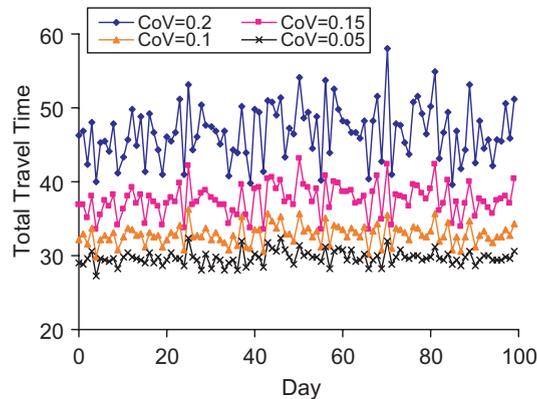


Fig. 3. Daily network total travel time (in vehicle-hours) over 100 days simulated under variable demand and supply conditions. Four levels of coefficient of variation (CoV = 0.5, 0.1, 0.15 and 0.2) are introduced to both the day-to-day demand (β_d) and the supply (β_s and β_v).

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

644 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
 645 total of 1000 days being simulated. Fig. 5 shows the frequency distribution of total network travel
 646 times by day over the 1000 days simulated. It can be seen that the distribution is skewed towards
 647 higher travel times, illustrating the existence of a small number of days with very high total travel
 648 time. These days, although relatively few, have a significant impact on the average result since
 649 they are not compensated by days with extremely small total travel time. Thus the mean travel
 650 time of 98.6 is significantly greater than the mode of 88.7 and the median of 95.0.

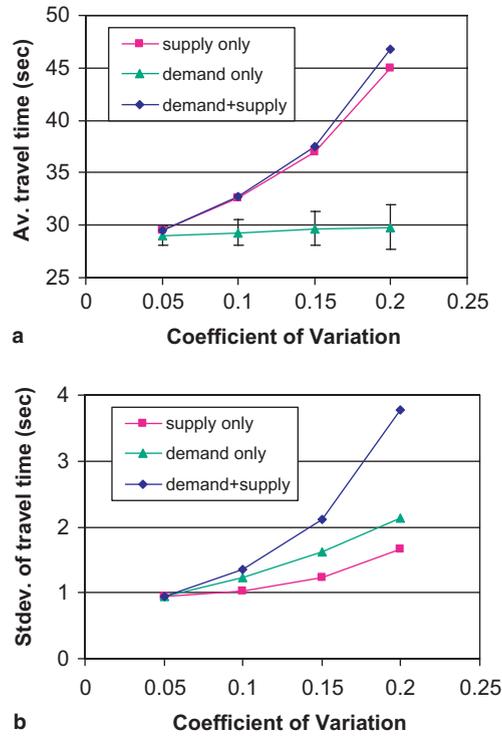


Fig. 4. Average (a) and standard deviation (b) in daily travel times as a function of demand and supply variability.

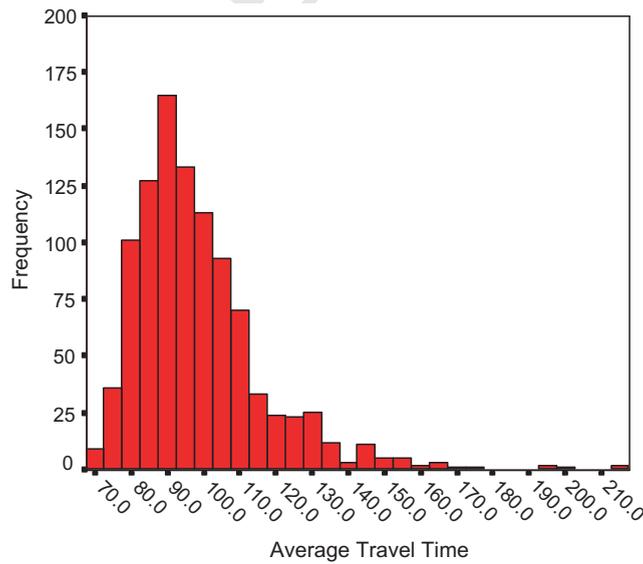


Fig. 5. Frequency distribution of average daily travel time (in vehicle-hours) for the Otley network, based on a simulation of 1000 days.

651 6.4. Responsive traffic signals

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

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

663 It can be seen that:

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

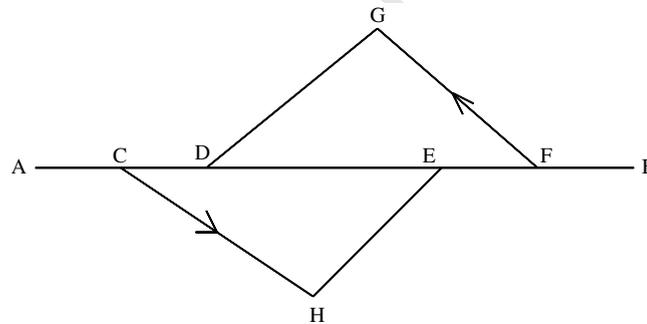


Fig. 6. The network for testing the signal control policies. Intersections C, D, E and F are signalised and the two O-D pairs are A to B and B to A. One-way streets are indicated by arrows.

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	

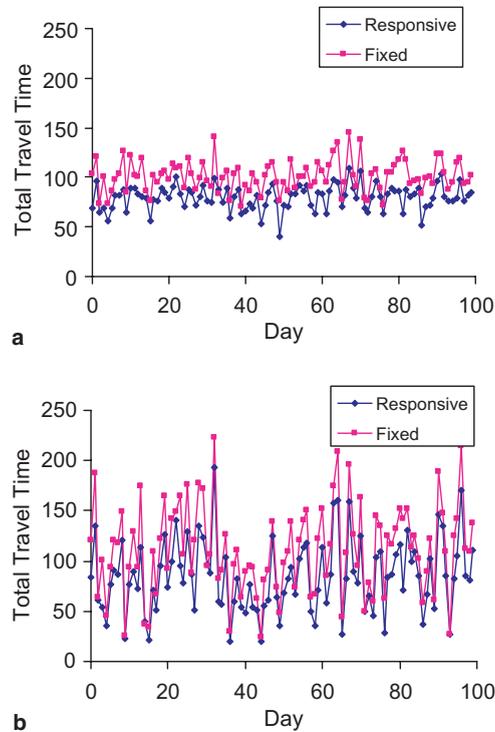


Fig. 7. Network total travel time under the fixed and the responsive signals, for demand variability of 5% (a) and 20% (b).

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

670
 671 The better travel performances produced by the responsive signals have also played an impor-
 672 tant role in drivers' route choice. Changes in signals were seen to attract drivers to the more direct
 673 routes. With the responsive plans all drivers were assigned to the two minimum distance routes by
 674 the end of 100 days, whereas with the fixed signal all four routes were used.

675 6.5. Scheme evaluation

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

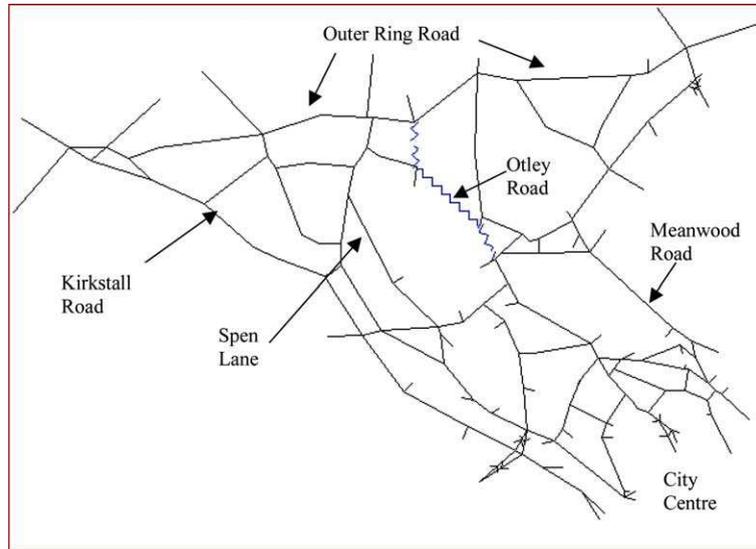


Fig. 8. The North Leeds network. The proposed bus-lanes run along the links shown as zigzag lines. One-way streets are indicated by arrows.

683 The proposed scheme introduces bus-only lanes on Otley Road inbound from the ring road to
684 Shaw Lane (shown as zigzag links in Fig. 8). The road space available to general traffic is hence
685 reduced from two lanes to one. The remaining lane is further narrowed to reduce the free-flow
686 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.

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

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

699 7. Conclusions

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

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

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

728 1950s, it is only more recently that serious momentum has begun to test alternative theories
729 against field data, beyond simple tests of aggregate consistency (Chakroborty and Kikuchi,
730 1999; Brackstone et al., 2002; Rakha and Crowther, 2003; Wu et al., 2003; Bham and Benekohal,
731 2004). We believe the continued study of field data to be one of the important priority areas for
732 future research in this area.

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