Evolution of adaptive route choice behaviour in drivers

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Abstract

Traffic assignment, the process by which vehicle origin-destination flows are loaded on to discrete paths traversing a road network, has been traditionally approached as a non-linear optimisation problem where it is expected that travellers will each minimise their own travel time. While such models are suitable for obtaining an `average' expected network state, traffic conditions on a day to day basis are inherently uncertain due to variations in travel patterns and incidents such as vehicle breakdowns, roadworks or bad weather resulting in fluctuations in realised traffic flows. Further, such models do not consider the transition from one `average' state to another when an aspect of infrastructure is changed such as a new road opening or the introduction of long term roadworks.

This paper therefore examines the evolution of driver route choice over time in stochastic time-dependent networks, specifically focusing on how individual experience of network conditions guides future decisions and its relationship with en-route switching opportunities. Existing algebraic and empirical models of route choice evolution are assessed (particularly using discrete whole path choices to assess benefits of information provision) and it is proposed that incorporating adaptive path routing based on expected correlations in traffic flow behaviour is more suitable than fixed path models for capturing the extent of observed uncertainty in network conditions.

We present this issue and explore through simulation a model where drivers adapt expected road link travel times for a given trip based on a combination of previous experience and discovered link travel times on that trip. We show how adaptive behaviour produces travel times which are on average faster than non-adaptive behaviour, confirming the potential of this modelling approach.

1.0 Background

Traffic assignment is the process by which expected trips between origin and destination zones, such as residential or business districts, are loaded on to a network representation of the transportation system under consideration. It provides a forecast of the demand placed on each transport link which can identify areas of congestion, travel times through a region, turning proportions at road intersections, expected revenues for charging schemes and other measurables (see Ortúzar and Willumsen, 2001 for an overview). The usefulness of behavioural models in the assignment process is that as well as investigating the current state of the network it is possible to develop predictions of how flows would vary given a different scenario or change to the system including new roads, population growth and infrequent special events such as sporting fixtures or urban evacuation.

Every traveller traversing a road network makes his or her route choice decision in response to their perceived expected state of the network. In the traditional context of traffic assignment it is assumed that a rational driver will adapt his or her route choice with a non-cooperative goal of minimising their own overall travel costs (Sheffi, 1989). Stochastic behavioural models are further capable of dealing with errors in perception and variation in response to cost savings. The difficulty with analysing flows within a transportation network is that the choices each driver makes have an impact on the rest of the system as, for example, high flows along a road link will cause congestion thereby increasing travel time and making that link appear less attractive in future trips. The theoretical outcome of these adjustments to route choice is that a situation is reached where no driver can reduce their own travel costs by switching routes. Accordingly the system finds itself in an unchanging `equilibrium' position as first proposed by Wardrop (1952) which is effectively a realisation of the game theoretic concept of `Nash equilibrium' in the context of traffic flows.

The expectation that at equilibrium all travellers moving between the same origin and destination points have equal journey costs has prompted assignment algorithms to be developed which are based on iterative loading (see Sheffi, 1989 for an introduction to techniques). Here, drivers are generally assigned to routes based initially on travel times in an empty road network (so the shortest path is preferable for all) and then proportional flows on each route are adjusted over proceeding iterations according to route travel times as determined by link performance functions, which determine the relationship between volume of traffic and the corresponding travel time on a given link. While the iterative process can be described as modelling route flows varying as drivers discover the equilibrium location, it is not the decisions of the individual travellers being explicitly modelled - rather aggregate flows are adjusted according to how an outside observer would expect flows to change.

Such techniques further assume that the system under consideration is an essentially static `average' flow description not varying over long periods of time. It is then impossible to capture how network flows behave between such equilibrium positions as individual drivers adapt their behaviour and behave in apparently suboptimal ways due to the instant lack of knowledge caused by system change such as new roads opening or road closures. Dynamic assignment models do consider driver behaviour over time (typically on a second by second basis over a number of hours, see Florian et al., 2008 for a recent review) and such models can consider opportunities for en-route rerouting and so can model localised delays and the effects of intelligent transportation systems (ITS) but generally do not feature explicit driver learning (Barceló, 2010).

It is asserted that one of the major issues in standard equilibrium based modelling, such as in those described above, is the lack of appreciation for modelling the varied between-day learning processes which impact traveller decisions, usually making them suboptimal. These drive the system out of equilibrium for a period after any network change occurs as drivers re-learn new or changed network characteristics. Such events include not only permanent changes, such as new roads, but also infrequent and unexpected congestion and delays.

1.1 Existing research regarding driver learning and route switching behaviour

A number of studies have investigated driver attitudes towards route choice over successive trips in competitive lab based experiments with participants (Iida et al., 1992, Selten et al., 2007, Ben-Elia and Shiftan, 2010, Lu et al., 2010). These have confirmed, in a controlled environment, that human route choice decisions do tend towards a single equilibrium position and have gone some way to quantify the impact of variable message signs and official information in influencing driver behaviour. It is generally found that if drivers have access to information of previous travel times on all routes through the network then flows do settle down to an (albeit noisy) equilibrium sooner than if only experienced travel times on their one chosen route is available (Selten et al., 2007).

Models have been developed which use agent based modelling and simulation approaches to model the actions of individual drivers' route choice decisions over successive trips, similar to dynamic models analysing traffic flows varying over the course of a single day by representing drivers individually (Horowitz, 1984, Liu and Huang, 2007, Wang and Sun, 2010, Tian et al., 2010). At present these only consider route choice on discrete paths rather than considering options for en-route rerouting or changes in departure time which dynamic within-day models are able to capture.

Here an agent based model is presented to represent drivers adapting expected road link travel times for a given trip en-route based on a combination of previous experience and discovered network conditions on that trip. The expectation of a shorter travel time, obtained by switching on to a potentially faster route, leads informed drivers to take advantage of such en-route switching opportunities and changing on to a different path through the network.

2.0 Traditional approaches for modelling route choice

The simple network shown in figure 1a is an example of a two route system consisting of two discrete links connecting a journey origin \`A' to a destination \`B', a simple case which has received much attention in research investigating the evolution of route choice (Katsikopoulos et al., 2002, Selten et al., 2007, Ben-Elia and Shiftan, 2010). Link \`performance functions', which model how travel time on each link in figure 1a, $t(v)$, varies given the number of vehicles wishing to travel along it, v, in figure 1b are based on the BPR (Bureau of Public Roads) link travel time function where constants chosen are similar to empirical values (Liu and Huang, 2007) though a time unit need not be specified throughout this work.

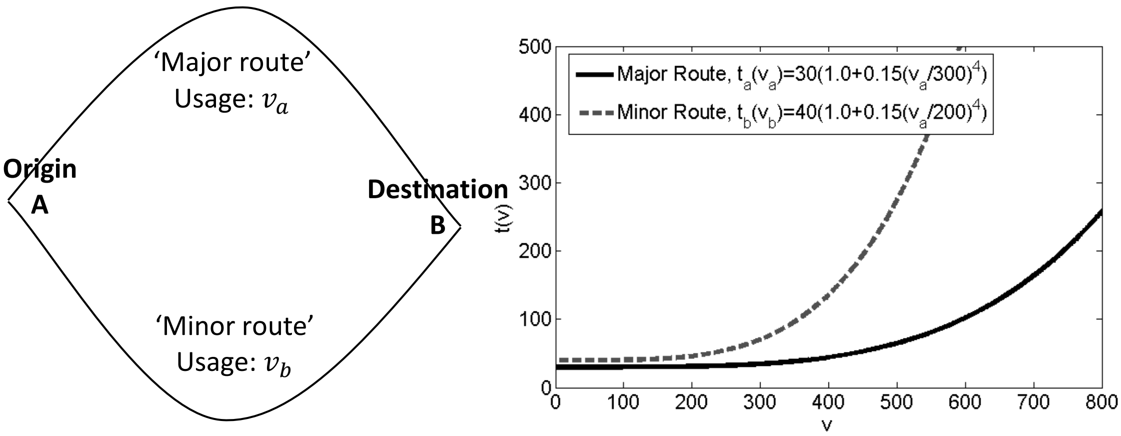

Figure 1a (left): Network structure and 1b (right): Link performance functions

The two routes can be categorised as a \`major route' and a \`minor route' because the performance profiles determine that the upper route in figure 1a can accommodate more vehicles with a lower travel time when compared against the minor route. Throughout this work travel time is the only factor which drivers are expected to consider when determining the \`generalised cost' of an option, which Outram and Thompson (1978) found to be a plausible expectation and Ortúzar and Willumsen (2001) assert still generally holds true.

As a brief illustrative example of assigning equilibrium flows, consider the assignment of 700 drivers travelling between A and B. Intuitively from figure 1b if all drivers chose the major route then a shorter travel time could be found by any driver switching to use the minor route so at equilibrium the flow is shared between the two routes. Straight forward equilibrium based assignment would therefore assign 700 drivers according to the solution of the simultaneous equations:

$$30\left(1+0.15\left(\frac{v_a}{300}\right)^4\right)=40\left(1+0.15\left(\frac{v_b}{200}\right)^4\right) \quad (1)$$

$$v_a+v_b=700 \quad (2)$$

which gives $v_a=454.304$ and $v_b=245.696$ with a travel time of 53.665 time units on each route.

Since equated route flows do not vary between days or within days this is known as \`static assignment' where no aspect of the system varies with time. For such a trivial system a more sophisticated algorithm to discover static equilibrium flows need not be used, however this approach becomes mathematically intractable as network structure becomes more complex. Algorithms such as the method of successive averages (MSA) use discrete choice models, such as derivations of the multinomial logit (see Frejinger, 2008 for an overview of discrete choice modelling of route choice) to assign flows on more complex networks.

As an example of the issues which are addressed here, consider a temporary reduction in speed limit along the major route. Given the formulations above it would be expected that, to compensate for a higher travel time on the major route, a number of drivers would switch on to the minor route so returning the system to equilibrium flows. Existing techniques tell us nothing of how flows adapt to this new equilibrium and how long this process would take so now a richer representation of driver knowledge is considered here.

2.1 Agent based assignment featuring explicit individual learning

Agent based models of route choice behaviour represent each driver individually as *`agents'* so the decision to choose one route rather than another is based on the expected travel time of each route according to each agent's (accumulated) heterogeneous knowledge. Once a trip has been completed the agent is able to update their expectation of travel time so adding the experience gained from that trip. The formulations of individual knowledge and route choice decision used here are the same as proposed in Liu and Huang (2007), Wang and Sun (2010) and Tian, Huang and Liu (2010).

To model the two route system each simulated driver should hold an expectation of the travel time on each route through the network, $\tau_r^{(i,t)}$ which is the perceived travel time by driver i on route r (belonging to the set of routes, R_w) between origin and destination pair w (belonging to the set of pairs W) on trip number t. A trip is defined as a single unidirectional journey from an origin to a destination so often in the study of commuter behaviour one trip equates to a journey to a workplace on a single day (such as in Selten et al., 2007).

An agent's `strategy', being the decision to choose a particular route, is determined by a straight forward logit function which determines the probability that a route r is chosen by agent i on trip $t+1$, $p_r^{(i,t+1)}$:

$$p_r^{(i,t+1)} = \frac{\exp(-\theta\tau_{rw}^{(i,t+1)})}{\sum_{j\in R_w}\exp(-\theta\tau_j^{(i,t+1)})}, r \in R_w, w \in W \qquad (3)$$

In this function θ is a scaling parameter which sets the sensitivity to a unit change in τ. At the end of a trip τ is updated according to the reinforcement learning model:

$$\tau_r^{(i,t+1)} = \alpha c_r^{(i,t+1)} + (1-\alpha)\tau_r^{(i,t)},\ \ \alpha \in [0,1], r \in R_w, w \in W \quad (4)$$

where α represents a learning rate and $c_r^{(i,t)}$ is the experienced travel time on trip t, calculated directly from the functions in figure 1b so varies with flows along each link and providing feedback from the decisions of other agents. As in reality, agents all play in `one shot' competitive games meaning that once all agents have decided upon a route choice, route travel times are calculated and agents are informed of the resulting $c_r^{(i,t)}$ for their given choice. Updating of route choice then occurs prior to the next round of the game.

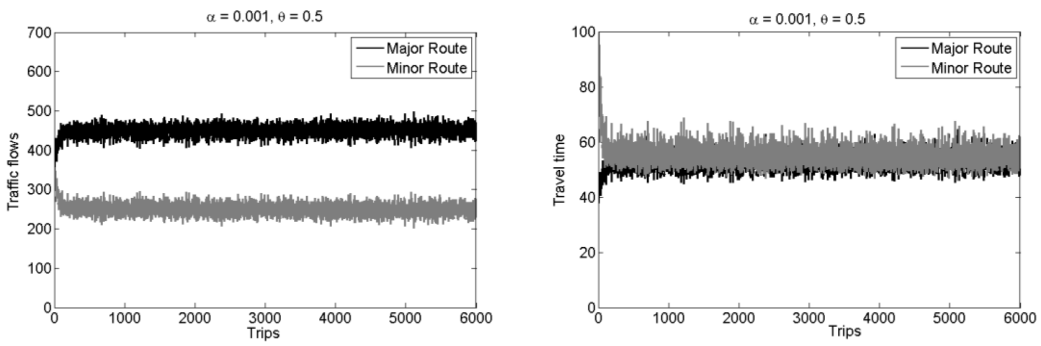

Figure 2a (left): Evolution of flows and figure 2b (right): travel time

Figure 2 shows the result of simulating 700 agents which are initialised with equal expectations of travel time on each route, so have no preference to choose one route over the other. Qualitatively these trends agree with those found by Liu and Huang, (2007) and

Wang and Sun (2010). After an initial period of exploration, flows within the closed system settle to an equilibrium position of approximately the same number of agents using each route as is found by the previously shown static assignment case.

Such agent based approaches are therefore suitable for describing individual learning on a static network so go some way towards answering the question of how flows evolve between trips. Crucially however this representation can also be used as a base for studying rerouting behaviour, where a traveller decides en-route to abandon their initial route choice and pursue an expected faster alternative based on experience accumulated over previous trips.

2.2 Agent based assignment in stochastic networks with en-route rerouting

Thus far the only known examples of using agent based assignment to investigate flow evolution in transport networks has been through simulation of whole discrete path choice as in section 2.1 and some extensions in to mode choice switching (Wang and Sun, 2010). A recent study has highlighted the impact of strategic en-route rerouting in response to variable message signs in a participant based lab experiment over consecutive trips (Lu et al., 2010).

`Strategic rerouting' is performed within trip in response to information gained prior to a route switching opportunity (see Gao et al., 2010 for further description). In the case of Lu, Gao and Ben-Elia's study this information was provided by a variable message sign placed prior to a junction in an experimental network similar to that described in figure 1. The variable message sign informs travellers whether a single link is `perturbed'. In this sense perturbed means a randomly occurring event giving rise to a deterministic increase in travel time - caused by factors such as an incident or bad weather - and modelled by the link adopting a `worse' performance function. Lu, Gao and Ben-Elia found evidence that drivers not only changed their route choice in response to this information when it was received, but were also likely to adapt their route choice in order to gain the information from passing the sign. Such information seeking behaviour has also been reported within a review of studies observing driver behaviour on `real world' road networks (Chorus et al., 2006).

Here the impact of en-route rerouting behaviour is explored based not on official information but instead from experience alone and the ability of drivers to infer downstream network state based on previously discovered correlations. Our network model, shown in figure 3, is an adaptation of the two route system as in figure 1, where the `major route' is now comprised of links 0 and 2 and the `minor route' is comprised of links 1 and 3. Two (low capacity) connector links – links 4 and 5– are added which enable travellers to switch between the major and the minor routes at the half way positions of each route.

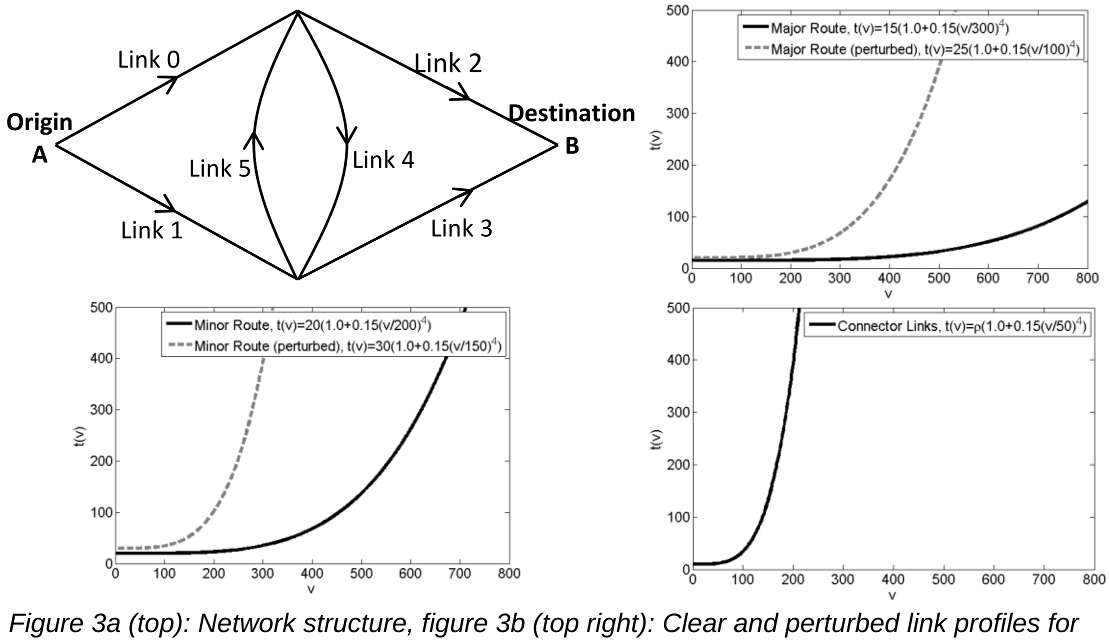

Figure 3a (top): Network structure, figure 3b (top right): Clear and perturbed link profiles for major route links, figure 3c (below left): link profiles for minor route links and figure 3d (below right): Link profile for connector links 4 and 5 with free flow travel time, $\rho = 10.0$

The model will be explored by adjusting the `cost of switching', being a linear measure of how much of a time penalty a driver incurs when switching between major and minor routes. This is represented by a variation of the free flow travel time, ρ, on the connector links as in figure 3d.

The four routes now traversing the network in figure 3 are:

First link	Second link	Third link	Route name
Link 0	Link 2	-	Route A (major route)
Link 0	Link 4	Link 3	Route B (major to minor route)
Link 1	Link 3	-	Route C (minor route)
Link 1	Link 5	Link 2	Route D (minor to major route)

Table 1. Description of routes through network shown in figure 3

Conditions are imposed under which the links forming the major and minor routes can become perturbed and adopt the `perturbed' link profile shown in figures 3b and 3c. In this model no form of pre-trip information is featured (such as social, internet, television or radio based advice) which could inform drivers of whether a link will be perturbed or not. The externally set conditional probabilities of links being perturbed are shown below. Notice that there is zero probability that downstream links (beyond the switching opportunities) become perturbed unless the upstream links on the same route (major or minor) are already perturbed. The notation $\mathrm{P}(L0p)$ is used to denote the probability that link 0 is perturbed and $\mathrm{P}(L0)$ is used to denote the probability that link 0 is clear.

$$P(L0p) = 0.1 \tag{5}$$

$$P(L2p|L0p) = 0.85 \tag{6}$$

$$P(L1p) = 0.15 \tag{7}$$

$$P(L3p|L1p) = 0.9 \tag{8}$$

In our model agents are initially unaware of both link travel times, as in the simple model described in section 2.1, and now also the correlations between perturbed link states on links as described above. As with real world drivers, agents here must form their own knowledge of network conditions, although it should be remembered that real world drivers usually have more information available to them than this `learn from direct experience alone' based approach such as signage and radio based advice. For simplicity it is also specified that drivers are aware that perturbations will only propagate downstream (towards the destination `B') so the expectation of links 0 and 1 being perturbed are independent of the expectation of perturbation on links 2 and 3.

As per our definition of `perturbed' links, being caused by observable effects such as bad weather or incidents, it is supposed that an agent, i, is aware when they have experienced perturbed conditions, and so can differentiate between unperturbed, $\gamma_l^{(i,t)}$, and perturbed, $\omega_l^{(i,t)}$, expected travel times for a given link, l on trip t. The update mechanism for both perturbed and unperturbed travel times remains the same as was previously proposed in section 2.1;

$$\gamma_l^{(i,t+1)} = \alpha c_l^{(i,t+1)} + (1-\alpha)\gamma_l^{(i,t)}, \ \alpha \in [0,1] \qquad \text{if link } l \text{ is not perturbed} \tag{9}$$

$$\omega_l^{(i,t+1)} = \alpha c_l^{(i,t+1)} + (1-\alpha)\omega_l^{(i,t)}, \ \alpha \in [0,1] \qquad \text{if link } l \text{ is perturbed} \tag{10}$$

The formulation of expected travel times for a given route now becomes more complex due to the stochastic nature of the network. The statistical independence of the probabilities of links 0 and 1 being perturbed means that an agent's expectation of these links being perturbed is simply given as the experienced fraction of the link i being perturbed, f_i:

$$P(L0p) = f_0, \quad P(L0) = 1 - f_0 \tag{11}$$

$$P(L1p) = f_1, \quad P(L1) = 1 - f_1 \tag{12}$$

To facilitate the learning of correlations between links which can become perturbed each agent is equipped with two correlation matrices of size NxN, where N is the number of links which can become perturbed, shown below.

$$\mathbf{D} = \begin{bmatrix} d_{0,0} & \cdots & d_{N-1,0} \\ \vdots & \ddots & \vdots \\ d_{0,N-1} & \cdots & d_{N-1,N-1} \end{bmatrix} \quad \mathbf{C} = \begin{bmatrix} c_{0,0} & \cdots & c_{N-1,0} \\ \vdots & \ddots & \vdots \\ c_{0,N-1} & \cdots & c_{N-1,N-1} \end{bmatrix} \tag{13}$$

Where $d_{i,j}$ is the correlation that link i is also perturbed given that link j is found to be. A value of $d_{i,j} = 1$ implies that link i is always perturbed when link j is and $d_{i,j} = 0$ implies no correlation so the relationship is random.

Similarly the `clear conditions' correlation matrix, **C**, behaves in the same manner except it models the correlation between link i being perturbed given that link j is experienced to be clear. A value of $c_{i,j} = 1$ implies that link i is always clear when link j is perturbed and $c_{i,j} = 0$ implies no correlation.

Every time an agent completes a trip the matrices **C** and **D** are updated with the experiences gained from that trip. If the relationship has been found that link i is perturbed given that link j is then +1 is added to the set of found relationships which inform $d_{i,j}$ and if the criterion is not met then a -1 is added. This is also the update mechanism for the **C** matrix. The specific values of $d_{i,j}$ and $c_{i,j}$ are then the mean average of this set (with the exception that this cannot return negative, if a correlation is found to be less than zero a value of 0.0 is returned).

The formulation of expectation of perturbations on downstream links is more of a challenge to implement since agents are unaware of the correlations which feature in perturbation propagation downstream. Using the assumption that perturbations can only propagate downstream the following equations can be used for determining the expected likelihood of the state of a downstream link, $\mathrm{E}[P(\ldots)]$, using the total probability theorem:

$$\begin{aligned} &\mathrm{E}[P(L2p)] = \\ &\mathrm{E}[P(L2p|L0, L1)] \cdot \mathrm{E}[P(L0, L1)] + \\ &\mathrm{E}[P(L2p|L0, L1p)] \cdot \mathrm{E}[P(L0, L1p)] + \\ &\mathrm{E}[P(L2p|L0p, L1)] \cdot \mathrm{E}[P(L0p, L1)] + \\ &\mathrm{E}[P(L2p|L0p, L1p)] \cdot \mathrm{E}[P(L0p, L1p)] \end{aligned} \tag{14}$$

The issue when trying to apply this model is that agents never have access to the knowledge relating to the state of links 0 and 1 simultaneously. Instead equation 14 can be rewritten to allow for the determination of the expected probability of a link being perturbed based on actual experience:

$$\begin{aligned} &2 \cdot \mathrm{E}[P(L2p)] = \\ &\mathrm{E}[P(L2p|L0)] \cdot \mathrm{E}[P(L0)] + \\ &\mathrm{E}[P(L2p|L0p)] \cdot \mathrm{E}[P(L0p)] + \\ &\mathrm{E}[P(L2p|L1)] \cdot \mathrm{E}[P(L1)] + \\ &\mathrm{E}[P(L2p|L1p)] \cdot \mathrm{E}[P(L1p)] \end{aligned} \tag{15}$$

$$\begin{aligned} &2 \cdot \mathrm{E}[P(L2p)] = \\ &c_{2,0} \cdot (1 - f_0) + \\ &d_{2,0} \cdot (f_0) + \\ &c_{2,1} \cdot (1 - f_1) + \\ &d_{2,1} \cdot (f_1) \end{aligned} \tag{16}$$

As equation 16 shows the expected probability of a downstream link being perturbed can now be calculated. Similarly the expectation of link 3 being perturbed is given as:

$$2 \cdot \mathrm{E}[P(L3p)] = c_{3,0} \cdot (1 - f_0) + d_{3,0} \cdot (f_0) + c_{3,1} \cdot (1 - f_1) + \ d_{3,1} \cdot (f_1) \tag{17}$$

The aim of this model is to allow agents to combine information accrued on previous trips with information obtained en-route in order to facilitate the possibility of an agent recognising that it would be more beneficial to switch routes than remain on a route which is experiencing perturbations which are expected to continue. Accordingly at the route switching opportunity agents re-evaluate route travel times given the conditions they have experienced.

$$2 \cdot \mathrm{E}[P(L2p)] = c_{2,0} \cdot 0 + d_{2,0} \cdot 1 + c_{2,1} \cdot (1 - f_1) + d_{2,1} \cdot f_1 \quad \text{If link 0 found perturbed} \tag{18}$$

$$2 \cdot \mathrm{E}[P(L2p)] = c_{2,0} \cdot 1 + d_{2,0} \cdot 0 + c_{2,1} \cdot (1 - f_1) + d_{2,1} \cdot f_1 \quad \text{If link 0 found clear} \tag{19}$$

$$2 \cdot \mathrm{E}[P(L2p)] = c_{2,0} \cdot (1 - f_0) + d_{2,0} \cdot f_0 + c_{2,1} \cdot 1 + d_{2,1} \cdot 0 \quad \text{If link 1 found clear} \tag{20}$$

$$2 \cdot \mathrm{E}[P(L2p)] = c_{2,0} \cdot (1 - f_0) + d_{2,0} \cdot f_0 + c_{2,1} \cdot 0 + d_{2,1} \cdot 1 \quad \text{If link 1 found perturbed} \tag{21}$$

Similarly for link 3:

$$2 \cdot \mathrm{E}[P(L3p)] = c_{3,0} \cdot 0 + d_{3,0} \cdot 1 + c_{3,1} \cdot (1 - f_1) + d_{3,1} \cdot f_1 \quad \text{If link 0 found perturbed} \tag{22}$$

$$2 \cdot \mathrm{E}[P(L3p)] = c_{3,0} \cdot 1 + d_{3,0} \cdot 0 + c_{3,1} \cdot (1 - f_1) + d_{3,1} \cdot f_1 \quad \text{If link 0 found clear} \tag{23}$$

$$2 \cdot \mathrm{E}[P(L3p)] = c_{3,0} \cdot (1 - f_0) + d_{3,0} \cdot f_0 + c_{3,1} \cdot 1 + d_{3,1} \cdot 0 \quad \text{If link 1 found clear} \tag{24}$$

$$2 \cdot \mathrm{E}[P(L3p)] = c_{3,0} \cdot (1 - f_0) + d_{3,0} \cdot f_0 + c_{3,1} \cdot 0 + d_{3,1} \cdot 1 \quad \text{If link 1 found perturbed} \tag{25}$$

When forming the expectation of link travel times, agents use the following formulation which creates an `average' expected travel time on a link, combining the expectation of a link being perturbed and the expected travel times given perturbations:

$$\begin{aligned} \tau_l^{(i,t)} &= \mathrm{E}[P(Llp)] \cdot \gamma_l^{(i,t+1)} + \mathrm{E}[P(Ll)] \cdot \omega_l^{(i,t+1)} \\ &= \mathrm{E}[P(Llp)] \cdot \gamma_l^{(i,t+1)} + (1 - \mathrm{E}[P(Llp)]) \cdot \omega_l^{(i,t+1)} \end{aligned} \tag{26}$$

The actual route choice decision is then based upon the simple logit model as in equation 3, where route travel times are found as the sums of expected travel time along links forming the whole route.

3.0 Result of simulation incorporating en-route rerouting opportunities

The simulation model was entirely developed in C# featuring a custom netlist parser which was supplied with a description of the network shown in figure 3 featuring link delay interdependencies specified in equations 5-8. 700 driver agents were initialised with naïve intelligence as is described in the model description in section 2.3 and allowed to evolve their route choice preferences over a period 6000 trips. The general results of a run of the simulation are shown in figure 4.

Figure 4 shows the outcome of our model facilitating route switching behaviour with $\alpha = 0.1$, $\beta = 0.01$ and $\rho = 10.0$. It shows that the system does reach the theoretical equilibrium position where agents begin their trip choosing to travel along the four routes. Clearly visible is that driver agents do take advantage of the route switching opportunities when a delay causing perturbation occurs, causing the large fluctuations in route flows after the switching opportunity. These fluctuations also generally correspond to drivers deserting the `major' or `minor' routes in favour of the other. One clear observation is that while at equilibrium one would not expect link 4 to handle any traffic at all, if the first half major route is delayed then approximately one fifth of all network traffic traverses link 4 because agents have learned that link 2 will probably also be perturbed and a shorter travel time can be found by diverting.

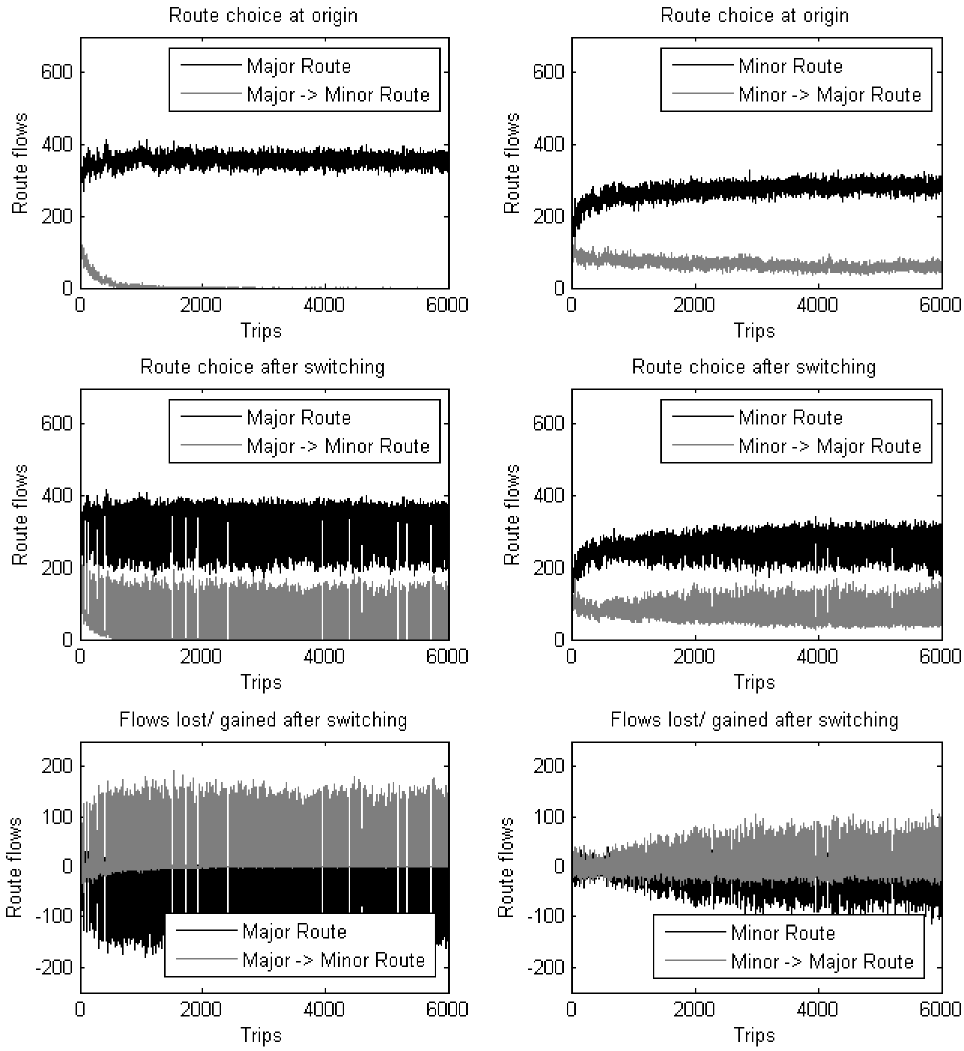

Figure 4. Flows varying across all four routes in a single simulation run with route switching

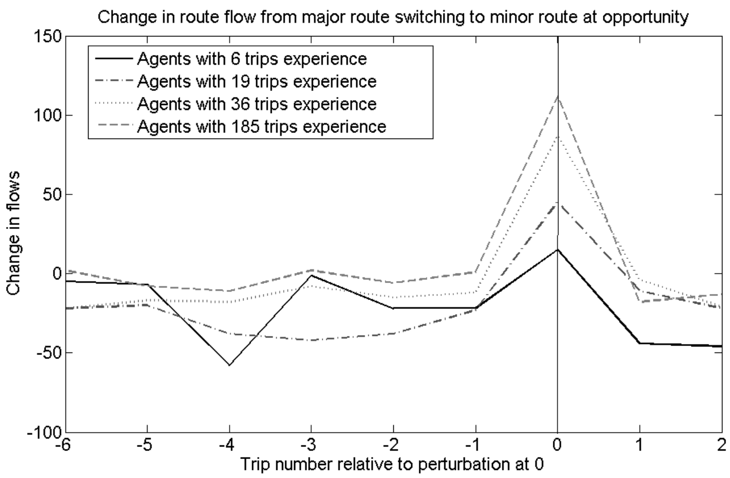

Figure 5. Change in flows relative to a perturbation at various trip numbers throughout the simulation

To illustrate the presence of evolution of switching behaviour figure 5 shows how flows switching between the `major route' (route A) to `major route to minor route' (route B) vary across trips leading up to a trip where a perturbation on link 0 (the first link of the major route) at trip 0 relative to a perturbation. Initially agents have no conception of the benefit of switching, so the experience of 6 trips line fluctuates more than at later periods and holds little or no response to the perturbation. As the time progresses more agents `learn' the benefit of switching to avoid expected perturbations, thus the spike increases.

The existence of four possible network configurations upstream of the switching opportunity results in four realised possible sets of equilibrium flows across the network:

Upstream Conditions	**Link 0**	**Link 1**	**Link 2**	**Link 3**	**Link 4**	**Link 5**
L0 clear, L1 clear	358.951	341.050	393.418	306.583	0.000	34.467
L0 clear, L1 perturbed	358.942	341.058	479.170	220.830	0.000	120.228
L0 perturbed, L1 clear	358.845	341.155	260.170	439.830	132.888	34.213
L0 perturbed, L1 perturbed	360.500	339.500	346.750	353.250	133.417	119.667

Table 2. Equilibrium network flows in the four possible network states prior to switching

Table 3 shows how the mean travel time for agents varies as the `cost of switching', $\rho$, is increased (discouraging use of `major to minor' and `minor to major' routes) and then when route switching is not available (so agents cannot adapt their route in response to perturbations). Clearly route switching is encouraged when agents are able to do so, as in this scenario a lower mean travel time is found.

Simulation experiment		**Mean travel time (units)**
ρ=10.0 (With switching)	Runs with 0 perturbed links	86.475
	Runs with 1+ perturbed links	446.420
	All 2000 runs at equilibrium	**172.502**
ρ=500.0 (With switching)	Runs with 0 perturbed links	89.477
	Runs with 1+ perturbed links	502.071
	All 2000 runs at equilibrium	**189.623**
ρ=10.0 (Without switching)	Runs with 0 perturbed links	95.177
	Runs with 1+ perturbed links	503.868
	All 2000 runs at equilibrium	**190.402**

Table 3. Mean travel times for agents in simulation runs with varying cost of switching

These results verify that a simulation model has been developed which illustrates that if drivers are equipped with the ability to learn the correlations between found delays on links, such that given a set of observable network conditions they are capable of inferring future conditions on the network, they can undertake strategic rerouting in order to avoid expected upcoming delays.

4.0 A different equilibrium?

Perhaps the key finding from this model is shown in figure 7, comparing the initial route choice equilibrium flows when varying the probability of link 0 being perturbed for both the non route switching and route switching behaviour. Since initial route choice is being examined here it can be assumed that these observations are valid for describing whole network flows on totally unperturbed trips (entirely clear days) as standard equilibrium models predict as described earlier.

Intuitively as the probability of link 0 being perturbed increases, the attractiveness of the entire major route (route A) falls (due to the correlation between upstream and downstream links) and at some probability the minor route (route C) becomes more appealing as an initial route choice. Figure 6 shows that when allowing switching the major route can actually remain the favoured choice for higher probabilities of perturbations occurring. This is because with route switching enabled agents *expect* a portion of others to switch off the major route in response to a perturbation, practically resulting in a lower expected perturbed link travel time, than if all agents using the major route are unable to switch.

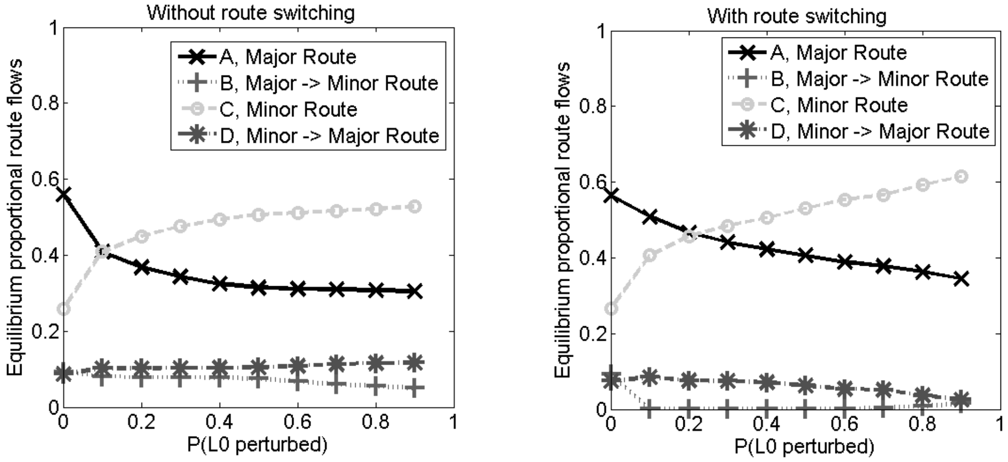

Figure 6a (left): Equilibrium whole route flows under non route switching behaviour and figure 6b (right): Equilibrium whole route flows with route switching capability

Although the major route (route A) remains more the more attractive route option for an extended period, found in figure 6, figure 7 shows how the corresponding flows on the major route upstream link 0 (figure 7a) and downstream link 2 (figure 7b) vary with the probability of perturbations occurring, taking in to account the impact of agents which start their journey intending to use routes B and D. Here link 0 flows are approximately the same for all variation in perturbation probability because in the `without switching' case a portion of travellers intend to switch on to the minor route (using route B), which does not occur in the `with switching' scenario. Accordingly in the `with switching' case flows are higher on link 2 because the proportion which use route B has already diverted along connector link 4.

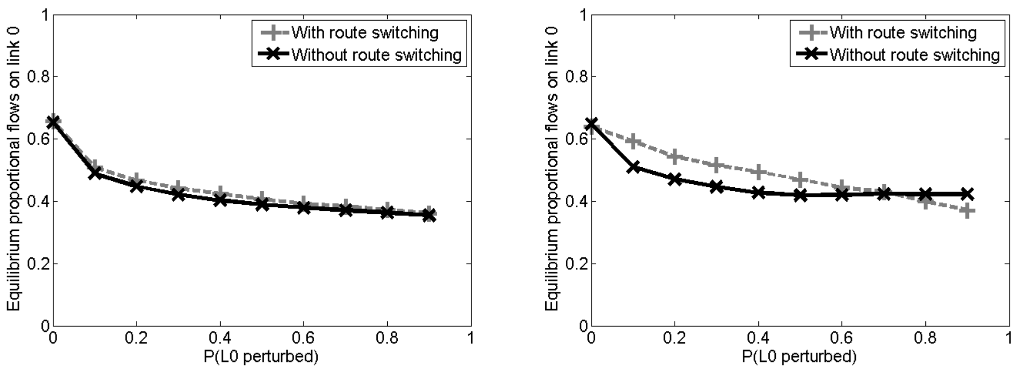

Figure 7a (left): Equilibrium flows on link 0 on unperturbed conditions and figure 7b (right): Equilibrium flows on link 2 in unperturbed conditions

5.0 Conclusions

By including the ability for travellers to divert in the presence of individually perturbed links, the network exists as a set of multiple (in this case, four) potential equilibrium flows, dependent on upstream conditions determining how travellers react to the perturbation configurations. It is not difficult to imagine such an outcome occurring in an urban network where drivers have one set of preferred routes given particular observable system conditions – such as no delays on a main carriageway – and a different set of preferred routes used given those conditions being different – such as delays or incidents occurring.

It has also been shown that the novelty in the approach of modelling switching behaviour is found in the observation that clear condition equilibrium flows are different when compared with modelling whole route choice, as existing equilibrium approaches do. This is because drivers are implicitly being modelled as reacting to risk and learn that even in perturbed conditions the option exists to switch away from a poor decision, whereas in the whole route choice case drivers are locked in to one path. Accordingly an extension to this model would be to incorporate observed (often counter-intuitive) reactions toward risk behaviour (see Katsikopoulos et al., 2002) rather than the `rational traveller' model presented here.

Generally, modelling the reactions of drivers to information gained en-route, and its relationship to knowledge held by drivers prior to beginning a trip, is important to understanding how flows vary in a transport system as has been shown here. Further, this includes not only correlations between stochastically perturbed roads, as explored here, but other information sources such as variable message signs, media outlets, social contacts or simply `variety seeking' which all count as viable extensions for research.

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