HIGHWAY RELIABILITY SUPPLY EFFECTS

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1.   INTRODUCTION

The Department of Transport is funding a substantial research
programme into urban congestion and the possible role of road
pricing. A key element of this research is the development of
a strategic road pricing model (APRIL) to enable the impact
of alternative road pricing proposals to be evaluated.

To enable travellers' responses to road pricing to be
assessed (e.g. change of mode, time of travel, route,
destination etc.) APRIL has been specified to be sensitive to
a number of attributes of travellers and of the 'supply
system' - in particular, the highway network model.

One factor which is perceived to influence demand is travel
time reliability. APRIL's formulation, based on generalised
cost concepts, was therefore extended to incorporate a
reliability indicator, the precise nature of which was to be
derived through empirical research.

The Department of Transport commissioned Steer Davies Gleave
with the Transportation Research Group at the University of
Southampton to undertake a three-month research project into
highway travel time reliability and its supply effects. This
paper describes our findings and conclusions.   The
methodology adopted covers the following stages:

(a)   A general review of research on travel time reliability
      and its relationship with supply and demand; this is
      summarised in section 2 of this paper.
(b)   The development of a suitable simulation model to
      explore the effects of congestion and changes in supply
      characteristics of travel time variability; this would
      enable the team to test different functional forms and
      select the most suitable one for incorporation into
      APRIL; this is described in section 3.
(c)   The design and implementation of a limited survey in
      London to refine calibration of the model form selected
      as a result of (b); this survey and the resulting
      calibration and validation of the model are reported in
      section 4.

(d) To draw conclusions from the research, as reported in section 5.

2. REVIEW

The first phase of the study involved a detailed literature review to identify previous studies concerned with journey time variability and its prediction. In particular, the review was aimed at identifying:

(a) Possible traffic and network indicators for inclusion in the models and,

(b) Typical levels of journey time variability for comparison with the results predicted from the subsequent modelling work.

2.1 Sources of Travel Time Variability

Travel times in urban areas are governed largely by (i) drivers' desired speeds, (ii) speed limits, (iii) speed/flow effects on links and (iv) link/junction capacities. For cities like London, drivers' speeds are influenced by speed limits, although, some "inter-vehicle" variability in travel time can still occur due to differences in driver styles and vehicle type. Other causes of such variability can be related to junction operations such as the arrival time at signals relative to the signal aspect and to characteristics of the road, e.g. loading/unloading of lorries, parking and pedestrian movements.

However, a key factor affecting travel times and their variability is the level of congestion, which itself depends on the relationship between demand and capacity (supply). Factors which influence demand include time of day (travel to and from work), day of the week (working days, Fridays) and time of year (influenced by holidays, school terms etc.). Factors which influence supply include weather conditions (e.g. rain and fog), lighting conditions and incidents such as accidents, breakdowns, signal failures and roadworks.

2.2 Previous Studies

A number of surveys have been undertaken in London to measure travel times and associated variabilities on selected routes. All studies reflect between-day variability, and most reflect inter-vehicle and within-day variability to some extent. Key findings are that:

(i) The coefficient of variation (CoV) of travel time, i.e. the ratio of standard deviation to the mean, increases with reducing average speed. Thus, variability increases with increasing congestion. For example, early work by Smeed (1968) indicated CoV values of 0.33, 0.70 and 2.30

at 20, 10 and 5 mph speeds respectively. In later work (Smeed and Jeffcoate, 1971), CoV values ranging from 0.11 to 0.15 for mean journey times of between 62 and 79 minutes, corresponding to different starting times in a peak period, were recorded.

(ii) For current average speeds in central London of 10-12mph, the typical CoV found on one route was 0.15 to 0.20 for journeys on repeated days with the same start time (excluding journeys affected by incidents).

Surveys have also been carried out in Leeds (Montgomery and May, 1987). Analysing journey time variability on five radial routes in Leeds, they developed explanatory models to predict mean travel time. These models explained up to half the within-day and between-day variability in terms of lagged flow (ie. flow over the previous 30 minutes) and up to half the remaining variability in terms of time during the peak, day of week, season, visibility and weather. From 170 time periods of data, 59 had CoV values of 0.10 or less while 105 had values of 0.15 or less.

3. MODELLING

The second phase of the study involved the use of network modelling to generate a database of typical journey time variability for origin-destination (O-D) movements from which generalised predictive models for journey time variability would be produced.

The key requirements for the model were that it should adequately reflect time-varying demand, queuing and congestion, and provide journey time predictions for individual O-D pairs so that both within-day and between-day variability could be monitored. The model had also to be well-established, with proven capabilities for dynamic assignment and junction/link modelling on a network of sufficient size for the study. These requirements led to the selection of CONTRAM (Leonard et al, 1989), and its incident-derivative, CONTRAMI (University of Southampton, 1992), for use in the study.

3.1 CONTRAM and CONTRAMI

CONTRAM is a dynamic traffic assignment model developed at the Transport Research Laboratory (TRL) and typically used for the assessment of traffic management schemes in urban networks. CONTRAM uses a 'packet-based' assignment approach in which packets (i.e. groups of vehicles) are assigned to their optimal routes taking account of the dynamic traffic conditions encountered on those routes. Packet size can be reduced to one, for individual vehicle modelling, and a flexible generalised cost equation can be used for assignment.

CONTRAM is often used to model time-varying conditions within a peak period and it then reflects within-day travel time variability for that time period. Different time periods can then be modelled separately, as required. However, the assignment process produces results which can be interpreted as being a long-term average for conditions in that time period, and between-day variability is not explicitly reflected. For the purpose of this study, it was important to reflect travel time variability for drivers undertaking repeated trips at a similar time on different days (eg. commuting trips). New techniques were therefore developed within CONTRAM to model this between-day variability as described in section 3.3.

The 'incident version' of CONTRAM - CONTRAMI - has also been available to this study. CONTRAMI was developed by the University of Southampton for TRL to better reflect vehicle routing and network performance in incident conditions, when the equilibrium assumption of "perfect" knowledge of traffic conditions becomes inappropriate. CONTRAMI loads routes from the normal (equilibrium) case and these remain fixed when modelling an incident, except that regular drivers can divert at any junction if they encounter an unexpected queue ahead and if a reasonable alternative route exists.

3.2   The Network

The network used in this study was a CONTRAM model of an area of inner London (north), used by Sir Alexander Gibb & Partners in a contract for DoT/TRL concerning modelling the effects of the pilot Red Route. The model was based on a larger SATURN model developed during the East London Assessment Study (ELAS) and covered a morning peak period (0800-0900hrs).

The network area is defined by the River Thames to the south, the A102(M) to the east, the North Circular to the north and Euston Station to the west. This represents an area of around 100 sq kms, with trip lengths of up to 15 kms. Network congestion is high in this part of London. The average network speed in the time periods modelled was 14 km/hr.

The network consists of over 1600 links (of which over 50% are signal controlled), 560 junctions and 195 Origins/Destinations.

3.3   Methodology

The key requirements of the modelling were that it should be possible to represent the main causes of between-day journey time variability and that, by suitably combining runs of different scenarios, a reasonable representation of journey

time variability could be obtained for a large variety of O-D movements in the network. The modelling was aimed at generating indicators of the main factors affecting journey time variability, and typical trends, with calibration being subsequently achieved from surveys. Three main causes of journey time variability were identified for representation in the modelling:

(i)   day-to-day fluctuations in demand,
(ii)   environmental effects on capacity,
(iii)   traffic incidents.

<u>Random</u> between-day variability in demand was generated following a procedure adopted by the MVA Consultancy (1989) in an earlier study. This involved attributing a normal distribution to each O-D demand level, in which the variance was set equal to the mean, and randomly sampling from this distribution to produce a 'new' O-D demand. This produced a mean and variance of the percentage change in demand of 0% and 18% respectively when averaged across all O-D pairs. This procedure was repeated several times, using different random numbers, to produce a set of randomly differing O-D demand files. <u>Systematic</u> between-day variability in demand was introduced by applying a multiplying factor to all O-D demand levels (ie. factors of 0.94, 0.97. 1.03 and 1.06). Environmental effects on capacity were introduced by reducing junction saturation flows by 6% to account for the effects of wet weather, as reported by Kimber et al (1987) for traffic signals.

Aside from the availability of CONTRAMI, a further enhancement was made to CONTRAM to allow between-day variability in minor incidents to be reflected. Although empirical evidence is scarce, experience suggests that repeated minor incidents - illegal parking, short breakdowns and so forth - are an important contributory cause of between-day travel time variability. This enhancement consisted of introducing random (but constrained) saturation flow reductions on around 50% of links, which gave an average decrease in capacity (for those links affected) of around 5% (with a range of between 1% and 20%). Different random samples were taken to produce a set of randomly differing saturation flow conditions.

3.4 <u>Analysis</u>

The average route journey time for 2000 selected O-D pairs for one time period was recorded for each of the CONTRAM runs indicated above. The standard deviation of the route journey time was calculated for each O-D pair from this data set. These standard deviations then formed the <u>dependent variable</u> for the subsequent multivariate analyses.

The selection of 2000 O-D pairs gave rise to a large database, incorporating a variety of trip attributes:

(i)   different levels of congestion;
(ii)   a mixture of trip lengths;
(iii)   trips in 'inner'/'outer' London;
(iv)   radial/orbital routes.

The independent variables considered were largely constrained by the need for compatibility with APRIL - for this reason variables, such as lagged flows, which were suggested from the literature review, could not readily be used here. The variables chosen were free flow travel time (FFTT), delay (JT-FFTT) and a congestion index (CI = JT/FFTT), where JT is journey time. Many trips incorporated a mixture of inner/outer and radial/orbital links, and it proved impractical to attempt to separate these with the network available. 'Atypical' trips with a journey time of less than 2 minutes, or a congestion index of more than 5 were discarded from the database.

3.5 Results

The relationships between travel time variability and the proposed explanatory variables are shown in the following figures:

Figure 1 - Standard deviation of JT v Congestion Index
Figure 2 - Standard deviation of JT v Free Flow Travel Time
Figure 3 - Standard deviation of JT v Delay

where each data point represents a different O-D pair.

It can be seen from these figures that there is considerable scatter in the data indicating that no one variable by itself is able to explain most of the travel time variability. Conceptually, it may be expected that the standard deviation of travel time (σ) should increase with increasing CI. This is consistent with the results of Smeed (1968), who reported increasing co-efficient of variability with reducing speed. It could be that, at high values of CI, increased congestion does not cause increased travel time variability perhaps because traffic has entered a 'forced flow' state. There is some indication of this in Figure 1, where, above a CI value of about 3, the data are particularly scattered and σ is not noticeably rising.

Figure 2 illustrates the highly scattered relationship between σ and FFTT. It was expected that σ would increase with increasing FFTT (which is also a proxy for route length). However, FFTT was found to explain only some 7% of travel time variability in this data set.

Figure 3 illustrates a positive trend between σ and delay. Also, there is evidence to suggest that the rate of increase of σ reduces as the level of delay increases.

Various linear and non-linear regression relationships were investigated. The following 4 model formulations gave the best results (values for coefficients are given in Table 1):

$$\sigma = \alpha(CI - 1) \tag{1}$$
$$\sigma = \alpha + \beta(CI - 1) + \gamma(FFTT) \tag{2}$$
$$\sigma = \alpha \, (FFTT)^\beta \, (CI - 1) \tag{3}$$
$$\sigma = \alpha(JT-FFTT)^\beta \tag{4}$$

The above models explained between 35% and 42% of the travel time variability found from the simulation runs. These models were then carried forward for calibration and final selection based on the survey results.

4.   SURVEYS

4.1   Survey Programme

The final phase of the study required calibration of the 'preferred' model (resulting from the CONTRAM runs) and subsequent validation of this model. To enable this, a programme of journey time surveys was undertaken by driving along a sample of those links represented in the network and noting the link travel times.

In total, 40 weekday AM peak survey runs were conducted. To ensure consistency, the surveys commenced at the same time each morning and covered the same route. Considerable care was taken to ensure that the selected route was representative of the wider network. It was recognised that it was almost impossible to have a network that would fully represent all possible journeys in the strategic model APRIL. Moreover, our survey measures link (and not journey) travel times and their variabilities; because of their nature it is not possible to associate APRIL links directly to either CONTRAM or real (surveyed) links. Therefore, the survey was designed so that trips of different length could be identified and modelled. We then hoped to develop models that would not depend on a particular distribution of journey lengths.

In total, 1,600 individual link times were recorded and were input in to a spreadsheet for analysis of their variance. The data were stored on a link-by-link basis thus enabling the analysis to be undertaken using single links or a combination of them. A key objective was to derive a model which was independent of the trip length distribution. In addition, the journey times relating to 5 of the 40 links were 'held back' to permit model validation at a later stage.

4.2 Results

The survey data were grouped into chains of 1, 3, 5 and 10 links. Regression relationships were obtained for each chain length for each of the four model formulations [1]-[4] which were proposed from the CONTRAM modelling.

The two linear models, [1] and [2], demonstrated coefficient values which increased as the number of links in the chain increased. This result was not unexpected. In urban areas, the majority of the delay takes place at junctions and therefore the number of them that are encountered in a route is likely to affect travel time variability. As such, models [1] and [2] were discounted.

Earlier regressions using the model form $\sigma = \alpha$ FFTT (CI − 1) revealed α values that decreased as the chain length increased. In an attempt to stabilise the α values, FFTT was raised to a power of less than one. After exploration using a range of power values the power of 0.87 was found to give the most consistent α values (Table 1 − model [3]). This result suggests that trip length, as a proxy for number of junctions in a route, has a multiplicative effect on travel time variability through the congestion index.

Model [4] (Table 1) was also found to meet the criteria of good fit (high R^2) and parameter stability. Both models [3] and [4] were strong candidates at this stage having the following attributes:

(i)   Relatively simple model forms, being based on parameters available in APRIL.
(ii)   The models are logical in that σ is zero when congestion (JT/FFTT) or delay (JT−FFTT) is zero and in that σ increases with increasing congestion and delay.
(iii)   The models are relatively insensitive to trip length.
(iv)   The models provide good overall fit to the floating car data and the model forms are supported by the simulation data.

Models [3] and [4] were validated against data not used in the calibration process. The results of this work showed that the model predictions for these links were consistent with the observations; for more details see Steer Davies Gleave (1993).

Model [3] was finally considered preferable to model [4] based on its predictions of CoV outside of the data ranges which were used to calibrate the models. The predictions given by model [3] were found to be similar to those found in

practice (Smeed,1968) whereas model [4] underpredicted CoV at high values of FFTT and CI.

4.3   Comparison of Survey and Simulation Results

The coefficients found for the survey results were significantly different from those found from the simulation results. Reasons for the differences include

- Modelling errors inherent to any simulation and, in particular,
- Errors in generating travel time variability (for which there is no proven or generally accepted method).
- For reasons of cost the survey runs could not cover the full range of link types and traffic conditions which were modelled. The more condensed scatter in the survey data and, consequently, the lower unexplained variability was, therefore, to be expected.

An encouraging aspect of the comparison of simulation and floating car results is the similarity in the absolute values of σ predicted/recorded and the existence of similar trends in relationships between σ and the explanatory variables CI, FFTT and JT. Differences are most marked in the regression coefficients (Table 1). The main deficiency in the modelling appears to be the underprediction of variability at high values of congestion/delay; Table 2 shows predictions of σ and CoV using model [4] (model [3] gives similar results) for a range of values of JT and FFTT. Where delay is high, the simulation predictions of CoV are considerably lower than floating car predictions and are at the lower end of the range 0.1-0.2 found in other studies (Smeed, 1968).

5.   CONCLUSIONS

Research has been undertaken to identify simple models to incorporate travel time variability into fairly conventional transport models.   The strategic model for road pricing, APRIL, uses an extended generalised cost formulation where travel time variability is an additional cost element; this treatment is supported by research into the behavioural responses to travel time variability.

Alternative functional forms for modelling the supply side of this formulation were explored using a combination of simulation work and detailed surveys in London. This work resulted in the development and calibration of the model form

$$\sigma = 0.9FFTT^{0.87} (CI-1)$$

This model offers a simple form for relating the standard deviation of travel time to network conditions and is relatively insensitive to trip length, therefore offering

promise for adaptation to environments different from London. One advantage of this treatment is that journey time variability can be estimated after assignment and then incorporated into other choice models (time of day, mode, destination choice). Complex interactions between congestion, travel time variability and route choice are then avoided.

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TABLE 1 : REGRESSION RELATIONSHIPS

Model No.	Model	R^2
	SIMULATION	
1	$\sigma = 131 \ (CI - 1)$	35%
2	$\sigma = 98 \ CI + 0.07FFTT - 97$	42%
3	$\sigma = 37FFTT^{0.2} \ (CI-1)$	39%
4	$\sigma = 13 \ (JT-FFTT)^{0.4}$	40%
	SURVEY	
3	$\sigma = 0.9FFTT^{0.87} \ (CI-1)$	88%
4	$\sigma = 2 \ (JT-FFTT)^{0.75}$	94%

Notes:

1. The coefficient of determination (R^2) is defined as:
    $$R^2 = 1 - (RSS/TSS)$$
    where,   RSS = the residual sum of squares, and
               TSS = the total sum of squares.

2. Data ranges for the simulation data were: $1 < CI < 3$,
    $120 < FFTT < 2000$ seconds and $140 < JT < 4200$ seconds.

    Data ranges for the survey data were: $1 < CI < 3$,
    $6 < FFTT < 360$ seconds and $12 < JT < 1000$ seconds.
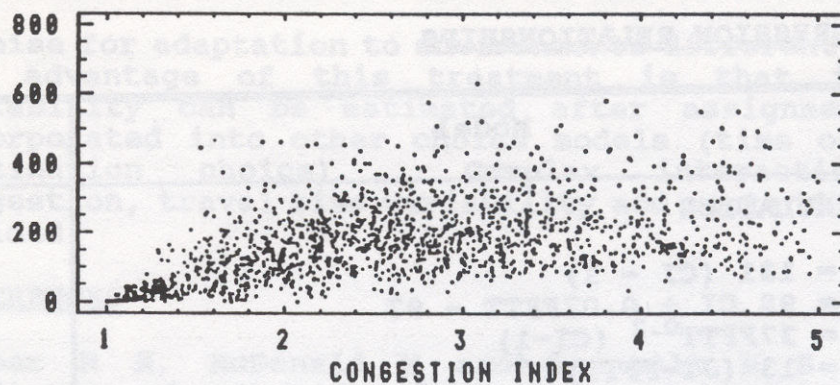
TABLE 2 : PREDICTIONS OF JOURNEY TIME VARIABILITY

JT (secs)	FFTT (secs)	CI	JT-FFTT (secs)	Predicted σ (CoV) Survey[1]	Simulation[2]
450	300	1.5	150	86 (0.19)	96 (0.21)
600	300	2	300	144 (0.24)	127 (0.21)
900	300	3	600	242 (0.27)	168 (0.19)
900	600	1.5	300	144 (0.16)	127 (0.14)
1200	600	2	600	242 (0.20)	168 (0.14)
1500	600	3	1200	408 (0.22)	222 (0.15)
1350	900	1.5	450	195 (0.14)	150 (0.11)
1800	900	2	900	328 (0.18)	198 (0.11)
2700	900	3	1800	553 (0.20)	261 (0.10)

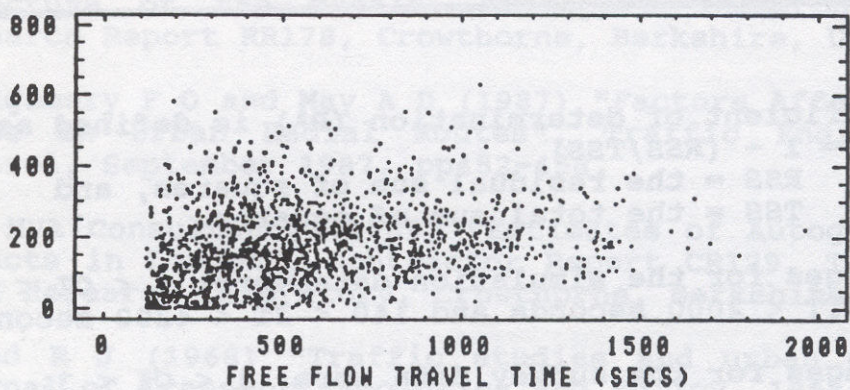[1] Model [4] based on floating car data: $\sigma=2(JT-FFTT)^{0.75}$
[2] Equivalent model based on simulation data: $\sigma=13(JT-FFTT)^{0.4}$

Figures in brackets are co-efficient of variation (σ/JT)

FIGURE 1 : σ v CONGESTION INDEX

FIGURE 2 : σ v FREE FLOW TRAVEL TIME

FIGURE 3 : σ v DELAY