FORECASTING AND APPRAISING TRAVEL TIME VARIABILITY IN URBAN AREAS

Clive Gilliam
(Hyder Consulting)
Teck Kean Chin
(Hyder Consulting)
Ian Black
(Independent Consultant)
John Fearon
(John Fearon Consultancy)

1 Introduction

Recent years have seen a growing interest in monitoring Travel Time Variability (TTV) on the highway network and developing methods to forecast TTV. This paper describes work carried out recently for the Department for Transport (DfT) in the United Kingdom, to develop methods for estimating and forecasting TTV using data collected from Global Positioning System (GPS) tracker equipped vehicles.

Primary data on vehicle location and time can be transformed into data on times taken to traverse different links on the road network. A database has been constructed comprising travel times for individual vehicles on 34 routes (up to 12 km long) within the 10 largest urban areas in England for a period of three years. This database on individual vehicles has been used to construct a TTV database containing data on the Standard Deviation (SD) of travel time along individual links in these routes as well as journeys comprising more than one consecutive links.

The paper discusses the quality of the database and its usefulness for monitoring TTV. It also explains the analysis undertaken to understand the impact on TTV of such factors as link/junction characteristics and journey length. This is followed by indications of appropriate relationships that can be used to predict TTV in urban areas.

Two types of analysis were performed: Single Link Analysis (SLA) which is based on data for individual links; and Multi Link Analysis (MLA) which utilises journeys covering a number of links. Each of these analyses was conducted using two sets of data:

- All records except those collected during weekends, school holidays and bank holidays (referred to as ‘Main Analysis’); and

- All records collected during August weekdays except those collected on bank holidays (referred to as ‘Holiday Period’).

Finally the paper demonstrates how changes in TTV can be incorporated into an assessment framework, thereby providing a monetary estimate of the forecast benefits due to changes in TTV following a policy or scheme intervention.

2 Background

With the aim of making practical progress in modelling TTV on urban highway networks, Arup et al (2002) re-analysed some travel time data collected for the London Congestion Charging programme in 1993. Since the data covered a route with some 40 separate links, it was possible to investigate a number of phenomena relating to journey length and the correlation of travel times between links.

A relationship for TTV was developed which had generally appealing properties, whereby the ratio of the SD of travel time to the mean travel time (Coefficient of Variation, *CV*) increases with the Congestion Index, *CI*, (the ratio of actual journey time to minimum or 'free flow' time), and decreases with journey length.

In order to investigate whether this relationship applied in other urban areas, a further survey was carried out in Leeds in 2003 and a similar analysis was undertaken. While the same functional form seemed to fit the data for both London and Leeds well, the parameters did reveal some differences between the two datasets, which required interpretation. Nevertheless, as a short-term measure, an appropriately averaged version of the model was developed to give estimates of TTV in urban conditions.

The recommended form of model forecasts the *CV* from distance (*d)* and *CI* terms for each origin (*i*) to destination (*j*) flow in the urban area using the following formulation:

$$CV_{ij} = 0.148 CI_{ij}^{\ 0.781} d_{ij}^{\ -0.285} \tag{1}$$

Application of the London model (to a hypothetical example) suggests that the time saving benefits of traffic management schemes which improve the use of existing capacity or of measures which reduce traffic volumes or increase capacity may be increased by around 20% when the benefits of the reliability improvements they deliver are taken into account.

The objective of the most recent study was to produce more robust TTV relationship using GPS data for 34 routes sampled for 10 major urban areas in England. It is intended that the relationships derived from this study will be used in the appraisal of transport initiatives which impact on highway supply and/or demand.

3 Data Preparation

ITIS/CJAMS (Congestion and Journey-time Acquisition and Monitoring System) collates and processes data provided by individual probe vehicles and a number of fleet management and tracking service providers.

The data collected includes information on GPS tracker equipped vehicles' location, speed and direction, which is reported at regular intervals while their ignition is switched on.

Using ITIS/CJAMS data, the analyses conducted in this research were based on the 10 largest urban areas in England as identified in DfT's Public Service Agreement (PSA) Target 4 (as listed in Table 1 below). A minimum of three routes within each of these urban areas have been selected – 34 routes in all.

Table 1 The 10 Largest Urban Areas in England

Area	Prefix
London	LO
Manchester	GM
West Midlands	WM
West Yorkshire	WY
South Yorkshire	SY
Tyne and Wear	TW
Merseyside	ME
Bristol	BR
Nottingham	NO
Leicester	LE

Routes were chosen to be typical for the urban areas for which the data is available. Six routes were chosen for London, three in each direction. For the other nine urban areas, the routes selected are for one direction only. Where possible, at least one non-radial route in each of the 10 urban areas has been selected.

Among the 34 selected routes, there are some short routes (less than 5 km) and a few routes where the average link length is greater than 700 metres. Over half the routes contain links in excess of 1 km in length. In addition, these routes contain sections which have speed limit of greater than 30 mph. These routes are representative of major urban roads which are of a higher standard and higher average speed limit than average urban roads.

The TTV observed in the ITIS/CJAMS data could arise from a combination of the following factors:
(a) Day-to-day variability (for an individual driver);
(b) Incidents;
(c) Variability over the survey period of 3½ years (i.e. due to a speed trend over time);
(d) Between-driver variability;
(e) Vehicles stopping for non-traffic reasons; and
(f) Data errors.

Given the data available it is not possible to differentiate between (a) and (b) which are true TTV and the other variability sources. However, observations far from the mean can have an unwarranted influence on the calculation of SD. It is important therefore to exclude these ‘outliers’. In principle the urban TTV model should exclude ‘outliers’ due to (c), (d), (e) and (f), but include those due to (a) and (b). The speed trend (c) will be small and given the sample size cannot be differentiated. Between-driver variability (d) is likely to be small in congested conditions and large in free flow conditions. Therefore, excluding (d) is desirable, but it is difficult to exclude (d) except for vehicles with very high speeds.

Two exclusion criteria were implemented in the research to eliminate the outliers:

1) Reject observations if the speed is greater than twice the speed limit or 100 mph, whichever is lower; and
2) Reject observations if the journey time falls outside ±4SD from the mean.

The vehicle types for which data is collected in ITIS/CJAMS includes Cars, Light Goods Vehicles (LGVs), Heavy Goods Vehicles (HGVs), Buses and Unknown Vehicles. These data were collected between January 2003 and August 2006.

For the purpose of this research, only records from Cars and LGVs (excluding breakdown recovery vehicles) have been utilised. Records collected during weekends, school holidays and bank holidays have been excluded from the ‘Main Analysis’. In addition, ‘outliers’ in the ITIS/CJAMS data were excluded before the analysis phase.

Table 2 shows the number of records for the selected routes available in the ITIS/CJAMS database. Over 50% of the total records are from Cars and LGVs (excluding breakdown recovery vehicles). Breakdown recovery vehicles represent about 10% of Cars and LGVs records for most of the routes, which reflects the vehicle type mix of the IT IS/CJAMS data. Around a third of these records were collected during school and bank holidays which are excluded from the ‘Main Analysis’. The ‘cleaned’ records are on average around 40% of the total records available.

Each route has at least an average of 30 records in each link for every timeslot between 07:00 and 22:00, although there are some individual links in a specific timeslot that have less than 10 records.

Table 2 Number of Records (between January 2003 and August 2006)

Route	Number of Records				
	All Vehicles	Cars and LGVs Only	Cars and LGVs* Only	Cars and LGVs* Only (excl. Weekends & Holidays)	Cars and LGVs* Only (excl. Weekends, Holidays & Outliers)
BR1	169551	113497	99061	61697	60987
BR3	176855	104399	97818	62093	61596
BR8	156624	92870	84447	54605	54004
GM3	247059	155036	142668	94480	93677
GM5	124531	109669	98890	64198	63078
GM10	25186	22107	19098	11825	11711
LE4	84702	54290	48947	31028	30834
LE9	131162	102275	90328	55363	54914
LE10	181013	133944	109247	68279	67873
LO2a	926387	788042	781450	433588	429810
LO2b	1035599	901688	895700	495938	491945
LO7a	1766942	1437055	1382990	781971	776179
LO7b	1847382	1483255	1415953	807884	801595
LO15a	446212	338571	307521	194696	193181
LO15b	474966	363844	323167	205805	204048
ME1	48476	36300	29318	18573	18424
ME2	65222	51705	46369	29671	29436
ME3	18236	15804	14926	9171	9100
NO1	185387	94707	79052	51644	51279
NO7	133927	113343	94960	58299	57810
NO9	204582	160414	128107	82550	81906
NO10	157612	118859	101234	64631	64281
SY7	150496	65126	50634	32331	32083
SY15	70417	65521	53868	31800	31526
SY20	198352	83793	75837	49894	49271
TW1	41888	34406	26944	16637	16499
TW9	49923	36781	32539	19274	19151
TW15	31968	23720	20112	12688	12598
WM4	412425	344797	299125	193918	192355
WM5	251981	207050	177806	110307	109492
WM19	857043	614202	572155	382673	379662
WY01	118155	71920	66202	41947	41597
WY11	145829	118322	109370	69811	69188
WY14	71240	42952	40415	25578	25330
TOTAL	11007330	8500264	7916258	4724847	4686420

* Excluded recovery vehicles

4 Single Link Analysis

The Single Link Analysis (SLA) examines the relationship between congestion and TTV on an individual link basis before examining journeys traversing more than one link.

Three relationships between Coefficient of Variation (*CV*), Congestion Index (*CI*) and Distance (*d*) were estimated in the SLA as follows:

- Single Link Elasticity:

$$CV_t = \alpha CI_t^{\beta}$$

$$\beta_r = \sum_{1}^{L_r} \frac{\beta_l}{L_r}$$

where L_r is the number of links on route r

The relationship is estimated for every link in the dataset. The average of all links on a route gives an estimate of Route Elasticity.

- Route Elasticity using Aggregated Single Link data:

$$CV_{lt} = \alpha CI_{lt}^{\beta}$$

where l refers to the link number (l = 1, l_r for route r)

The relationship is estimated for every route in the dataset by combining all links and all timeslots (between 07:00 and 22:00).

- Route Elasticity using Average link *CV*-Average link *CI*: $CV_{*_t} = \alpha \; CI_{*_t}{}^{\beta}$
  where * denotes average over all links (* = 1, N_r)

  The relationship is estimated for every route in the dataset using link CV and link CI average across all links in a route (for each timeslot).

For the calculation of the *CI* (the ratio of actual time to minimum or ‘free flow’ time) two times are required: an average travel time for a period; and a reference travel time (or ‘free flow’ travel time). The reference travel time is the travel time that could theoretically be achieved when traffic is free flowing. This is usually less than the speed limit in order to allow for slowing down at junctions and other alignment features. The reference travel time for each link has been derived from the average travel time using the ‘cleaned’ records collected between 00:00 and 06:00.

Because demand is higher, there is greater possibility of achieving good sample sizes in a short period of time during AM (07:00 to 10:00) and PM (16:00 to 19:00) peaks compared to the other time periods. As a result, each timeslot is set at 15 minutes for AM and PM peaks. For the rest of the day, each timeslot covers 30 minutes. The ‘cleaned’ records for each route have been allocated to the relevant timeslots using link entry time. Sixty timeslots have been defined in total.

4.1 Method 1: Single Link Elasticity

CV and *CI* for each timeslot have been calculated for every link in the selected routes. The relationship between *CV* and *CI* is as follows:

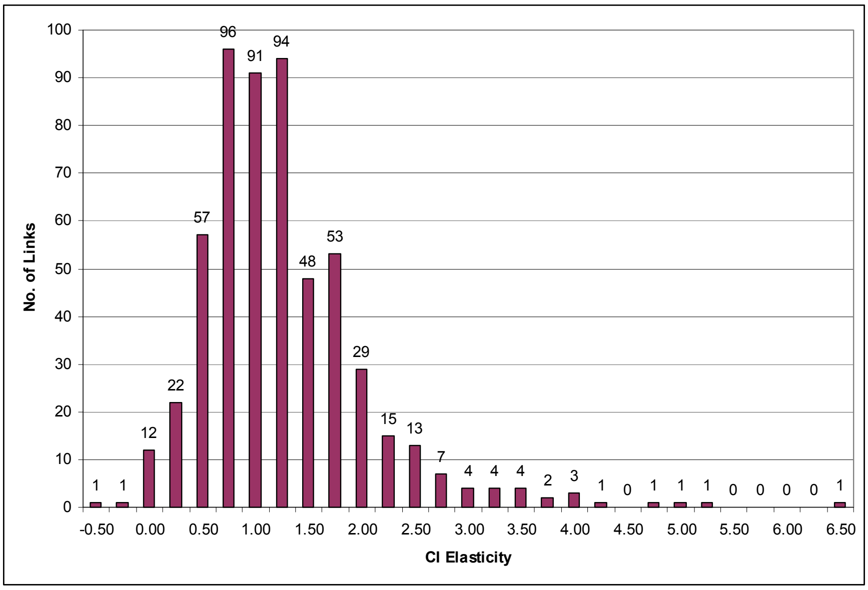
$$CV_t = \alpha \; CI_t^{\beta} \tag{2}$$

where α = Constant/Scale Factor
β = Elasticity: Coefficient for Congestion Index
t = Time Period (t = 1, T)

The *CI* elasticity estimated for each of the 561 links in the 34 routes ranges from -0.5 to 6.5. The average single link elasticity for the individual routes varies from 0.5 to 1.9. The average constant for all routes is 0.22 (σ = 0.03), and the average *CI* elasticity for all routes is 1.16 (σ = 0.32).

Figure 1 depicts the *CI* elasticity distribution for all links in the selected routes. Approximately 59% of the *CI* elasticities are between 0.5 and 1.5. For about 2.5% of links the *CI* elasticity is less than 0, and for around 3% the *CI* elasticity is greater than 3.

Figure 1 Histogram of *CI* Elasticity Distribution for All Links in the Selected Routes



4.2 Method 2: Route Elasticity using Aggregated Single Link Data

The previous section has described the results from the analysis of single links. For the analysis described in this section data from all links in a route are aggregated.

For each route under consideration, the single link *CV*, *CI* and *d* (in km) data for all links in every timeslot (between 07:00 and 22:00) are aggregated to carry out regression analysis to obtain the constant and elasticity.

This relationship is as follows:

$$CV_{lt} = \alpha \; CI_{lt}^{\beta} \; d_l^{\delta} \tag{3}$$

where α = Constant/Scale Factor
β = Elasticity: Coefficient for Congestion Index
δ = Elasticity: Coefficient for Distance
t = Time Period (t = 1, T)
l = Over all links (l = 1, l_r) for route r

The average Ordinary Least Squares (OLS) constant for all routes is 0.18 (σ = 0.03), the average OLS *CI* elasticity for all routes is 0.87 (σ = 0.19), and the average OLS elasticity of *d* for all routes is -0.23 (σ = 0.06). The averages weighted by number of links are 0.18, 0.82 and -0.22 respectively.

4.3 Method 3: Route Elasticity using Average Link CV - Average Link CI

An alternative way to examine the relationship between *CV* and *CI* for a route is to consider the average link *CV* and average link *CI* for each timeslot. The average data of a route is calculated using all link *CV*s and all link *CI*s (as those estimated in Section 4.1) respectively for the route under consideration.

Formally:

$$CV_{*_t} = \alpha \ CI_{*_t}{}^{\beta} \tag{4}$$

where α = Constant/Scale Factor
β = Elasticity: Coefficient for Congestion Index
t = Time Period (t = 1, T)
* = Average over all links (* = 1, N_r) for route r

The elasticity derived is again referred to as 'route elasticity' to indicate it refers to a particular route.

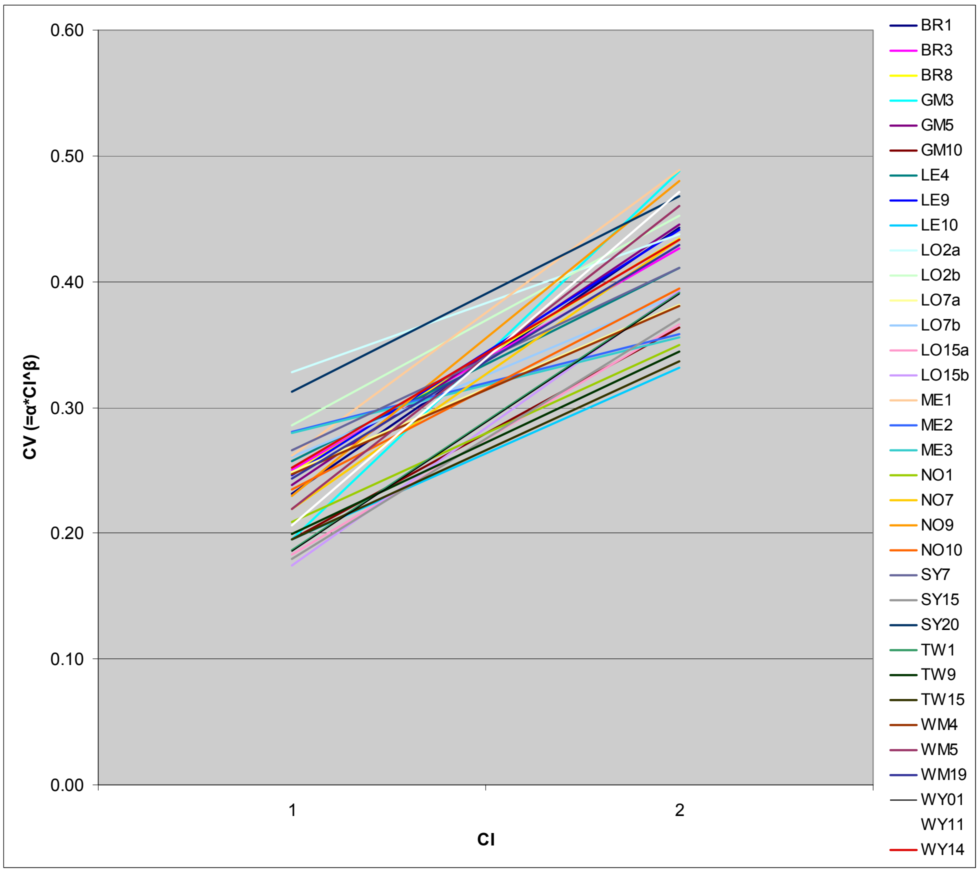
The constant and *CI* elasticity for each route are summarised in Table 3. The average constant for all routes is 0.23 (σ = 0.04), and the average *CI* elasticity for all routes is 0.82 (σ = 0.23). These figures are consistent with the average constant and *CI* elasticity figures found in the aggregated data.

Table 3 Route Elasticity Findings based on Average Link *CV* and Average Link *CI*

Route	Average Link CV-Average Link CI			
	Constant, α	Std Err of Coef α	Elasticity (CI), β	Std Err of Coef β
BR1	0.23	0.028	0.94	0.062
BR3	0.25	0.021	0.77	0.045
BR8	0.25	0.031	0.81	0.070
GM3	0.20	0.021	1.32	0.071
GM5	0.24	0.022	0.90	0.087
GM10	0.20	0.047	0.90	0.107
LE4	0.26	0.048	0.68	0.110
LE9	0.25	0.033	0.84	0.080
LE10	0.20	0.022	0.76	0.045
LO2a	0.33	0.015	0.41	0.028
LO2b	0.29	0.032	0.66	0.058
LO7a	0.25	0.014	0.62	0.024
LO7b	0.26	0.020	0.58	0.034
LO15a	0.18	0.031	1.00	0.053
LO15b	0.17	0.024	1.17	0.054
ME1	0.26	0.038	0.90	0.105
ME2	0.28	0.030	0.35	0.120
ME3	0.28	0.027	0.35	0.075
NO1	0.21	0.028	0.75	0.055
NO7	0.22	0.027	0.98	0.073
NO9	0.23	0.025	1.06	0.080
NO10	0.23	0.024	0.75	0.060
SY7	0.27	0.035	0.63	0.062
SY15	0.18	0.047	1.04	0.082
SY20	0.31	0.024	0.58	0.102
TW1	0.19	0.047	1.07	0.129
TW9	0.20	0.031	0.79	0.063
TW15	0.20	0.047	0.78	0.125
WM4	0.25	0.019	0.62	0.039
WM5	0.22	0.022	1.07	0.054
WM19	0.24	0.019	0.82	0.049
WY01	0.19	0.036	1.07	0.074
WY11	0.21	0.027	1.19	0.076
WY14	0.25	0.034	0.78	0.109
Average (Unweighted)	0.23	-	0.82	-
σ	0.04	-	0.23	-
Range	0.17 to 0.33	-	0.35 to 1.32	-
Average (Weighted by No. of Links)	0.24	-	0.81	-

In order to understand the error associated with using an average relationship (based on all routes) between congestion and TTV, rather than one that refers to the individual routes, it is necessary to examine how *CV* varies with *CI* on the different routes. Figure 2 illustrates *CV* (calculated using *Equation 4* and coefficients estimated from the respective routes) against *CI* by route, at *CI* = 1 and *CI* = 2.

Figure 2 *CV* (Calculated using *Equation 4* and Coefficients Estimated from the Respective Routes) against *CI* by Route



The graph shows variation between different routes. If an average relationship is used then the range of the individual routes around this can be referred to as a 95% confidence interval of ±33% and ±22% at *CI* = 1 and *CI* = 2 respectively. This can be regarded as the error likely to be associated with using an average relationship rather than one based on individual link characteristics.

4.4 CI Elasticity Comparison

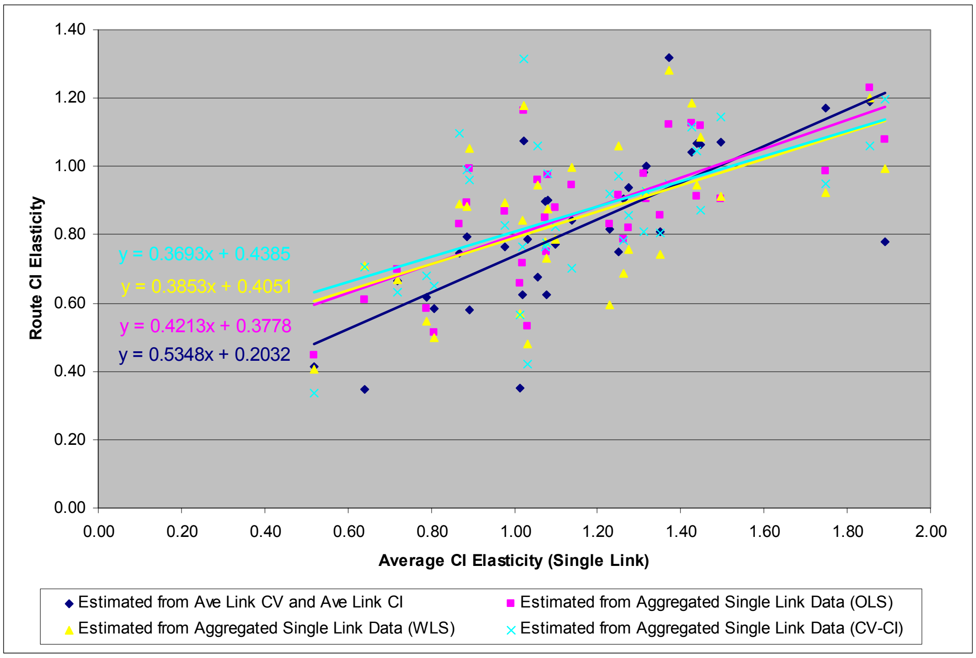
Previous sections employed three methods for examining average link elasticity on a route. These elasticities are compared graphically in this section.

Figure 3 shows route *CI* elasticity (estimated using both aggregated single link data, and average link *CV* and average link *CI*) against average *CI* elasticity. Along the horizontal axis are *CI* elasticities for every route estimated in Section 4.1. Along the vertical axis are *CI* elasticities for each route estimated in Sections 4.2 and 4.3. This graph suggests the route *CI* elasticities are always lower than the average *CI* elasticities.

The reason for this is the small number of very high elasticities (>3) estimated on some links that increases the average *CI* elasticity considerably. These high elasticities are where the *CI* only increases a little to around 1.5 (less than 2).

When data are aggregated by either method, these high elasticities do not have a big influence on the estimated route *CI* elasticity, and hence the route *CI* elasticities are lower than the average *CI* elasticity.

Figure 3 Route *CI* Elasticity against Average *CI* Elasticity



5 Multi Link Analysis

This section discusses the analysis undertaken for journeys comprising more than one link, i.e. Multi Link Analysis (MLA). The MLA extends the SLA to journeys (comprising more than one link).

Similar to the SLA, the reference travel time for each set of journeys has been derived from the average travel time collected between 00:00 and 06:00.

As the number of MLA observations is relatively low, forty-eight timeslots have been defined in the MLA as opposed to sixty in the SLA. Each timeslot covers 30 minutes in all time periods.

CV, *CI* and *d* for each timeslot have been calculated for every set of the MLA journeys in the selected routes. The hypothesised relationship between *CV*, *CI* and *d* is as follows:

$$CV_{jt} = \alpha CI_{jt}^{\beta} d_j^{\delta} \qquad (5)$$

where α = Constant/Scale Factor

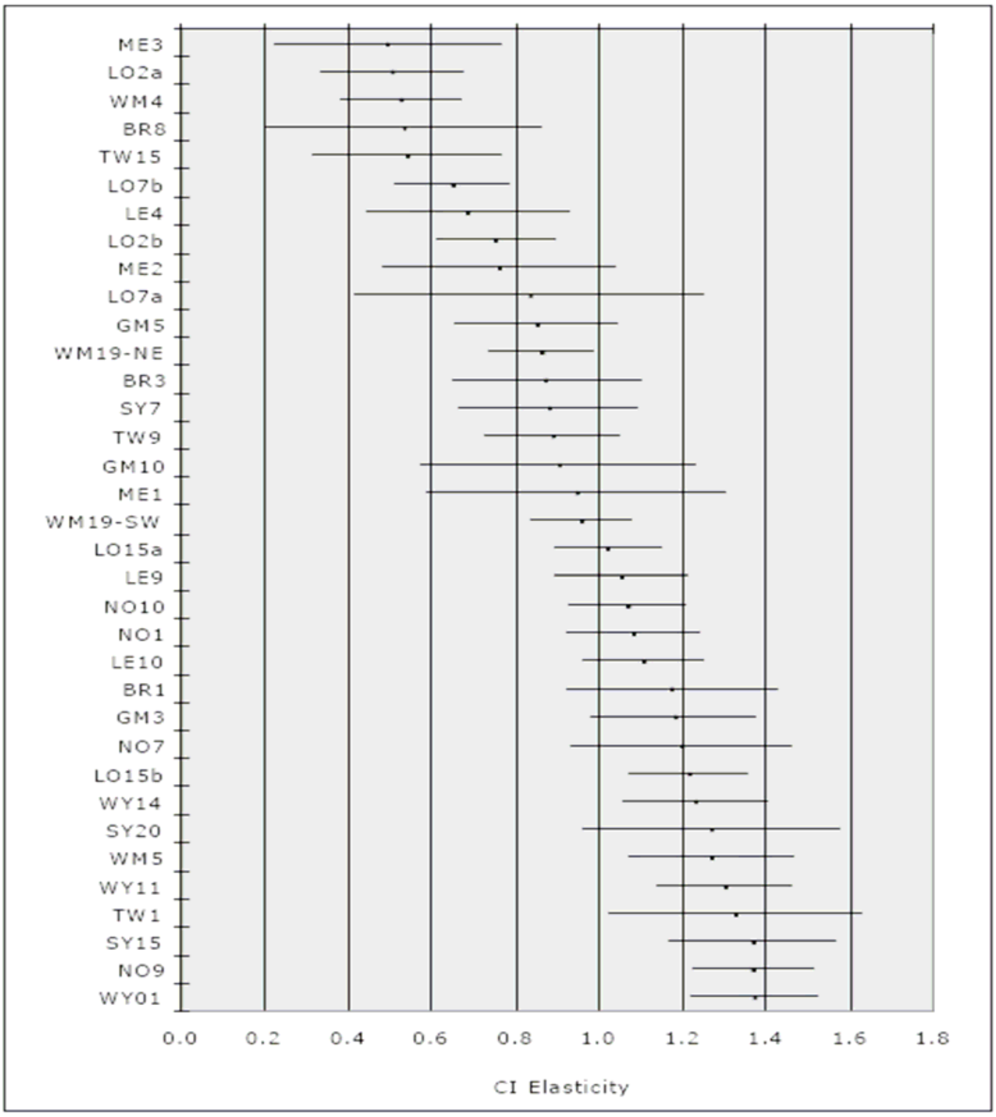
β = Elasticity: Coefficient for Congestion Index

δ = Elasticity: Coefficient for Distance
t = Time Period (t = 1, T)
j = Multi Link Journey

Both Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) regression analyses have been carried out to estimate α, β and δ. Data input to the regression analyses were *CV*, *CI* and *d*.

Figure 4 displays MLA *CI* elasticity (WLS) by route, together with the 95% confidence interval range. Similar to SLA results, the graph shows the relationships vary between urban areas and/or between different routes in urban areas.

Figure 4 *CI* Elasticity (Estimated using WLS) by Route



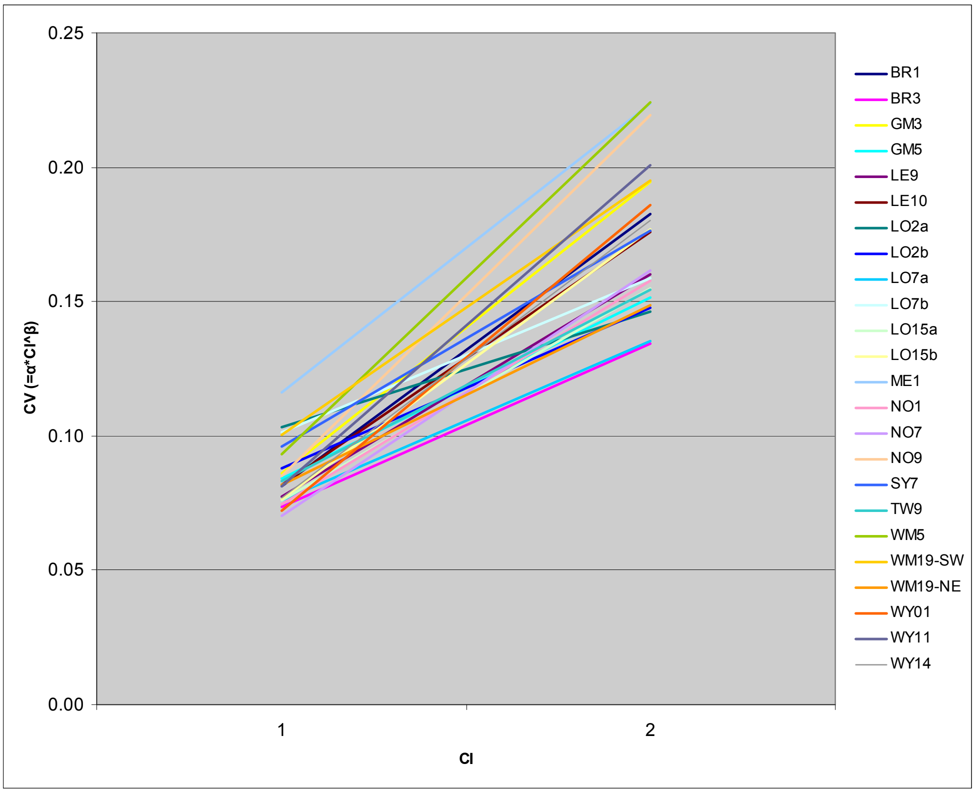
Some of the routes have very limited sample sizes for the MLA journeys which could influence the confidence level of the overall MLA result. For this reason, 11 routes have been eliminated from the analyses below (In general, routes that have a relatively high proportion of timeslots with less than 10 records are excluded from the analysis).

For the restricted sample of 24 routes using WLS, the constant varies from 0.12 to 0.19, the *CI* elasticity varies from 0.50 to 1.37 and *d* elasticity varies from -0.28 to -0.46. The unweighted average of these coefficients are constant 0.16 (σ = 0.02), *CI* elasticity 1.02 (σ = 0.23) and *d* elasticity -0.38 (σ = 0.05) and the averages weighted by 1/Standard Error are almost identical – 0.16, 1.02 and -0.39 respectively.

Figure 5 illustrates *CV* (calculated using *Equation 5* and WLS coefficients estimated from the respective routes in the restricted sample with *d* of 5 km) against *CI* by route, at *CI* = 1 and *CI* = 2.

The graph shows variation between different routes, with 95% confidence interval of ±27% and ±31% at *CI* = 1 and *CI* = 2 respectively. This confidence interval represents the error range to be expected if an average relationship is used rather than an individual relationship.

Figure 5 *CV* (Calculated using Equation 5 and WLS Coefficients, *d* = 5 km) against *CI* by Route – Restricted Sample Routes



5.1 *Additional Analysis Results*

The previous section estimated the multi link relationship between *CV*, *CI* and *d* using a combination of two data types – an average single link data and three multi link journeys. In order to examine influences due to average single link data, analyses in this section have been undertaken with only data from the multi link journeys which cover at least four links.

Regression analysis using the aggregated journey *CV*, *CI* and *d* from all or part of the 103 journeys have been combined in the regression analysis, without the average single links data. This method is referred to as 'aggregated'.

Table 4 shows the coefficients estimated from all 103 journeys, 72 journeys from the restricted sample routes and 65 journeys that have at least 60% of timeslots (between 07:00 to 22:00) contain 10 or more records respectively, using OLS and WLS regression analysis.

The constants and *d* elasticities in the WLS are consistent across all three datasets. *CI* elasticity in the restricted sample route is slightly higher than the other two datasets.

Table 4 MLA Findings using Aggregated Journey Data

	All Journeys		Restricted Samples		60% >= 10 records	
	OLS	WLS	OLS	WLS	OLS	WLS
Constant, α	0.17	0.16	0.17	0.16	0.16	0.16
Std Err of Coef α	0.025	0.014	0.026	0.015	0.020	0.016
Elasticity (CI), β	0.91	0.88	0.97	0.94	0.88	0.88
Std Err of Coef β	0.037	0.023	0.039	0.024	0.029	0.025
Elasticity (d), δ	-0.45	-0.37	-0.47	-0.40	-0.36	-0.34
Std Err of Coef δ	0.016	0.010	0.016	0.011	0.014	0.012

A third method that investigates the relationship between *CV* and *CI* is to consider the average of all constants and *CI* elasticities estimated for the 103 individual journeys. This method is referred to as 'average'.

For the 58 journeys in the restricted sample journeys (where journeys with high *CI* elasticity at low *CI* level have been excluded), the constant varies from 0.03 to 0.18 and *CI* elasticity varies from 0.14 to 2.45. The average of these coefficients unweighted are constant 0.09 (σ = 0.03) and *CI* elasticity 1.17 (σ = 0.50), and the averages weighted by 1/Standard Error are 0.10 and 1.12 respectively.

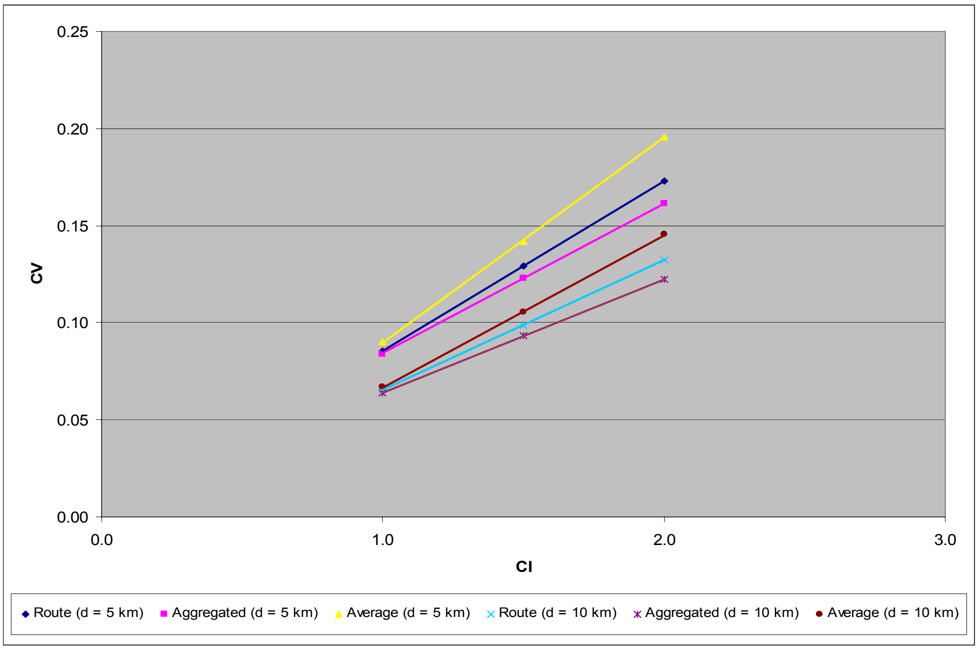
Table 5 summarises the coefficients estimated using three different methods discussed above. Constants and *d* elasticities estimated using all three methods are remarkably consistent. *CI* elasticity estimated in the 'aggregated' is lowest, followed by 'route', and 'average' has the highest *CI* elasticity.

Table 5 Summary Coefficients for 'Route', 'Aggregated' and 'Average' Methods

Coefficient	Route	Aggregated	Average
α	0.16	0.16	0.18
β	1.02	0.94	1.12
δ	-0.39	-0.40	-0.43

Figure 6 shows the *CV*s calculated using coefficients from Table 5 for *CI* = 1.0, 1.5 and 2.0, and *d* of 5 km and 10 km. It shows that the coefficients estimated by the 'route' method tend to provide a central value.

Figure 6 *CV* against *CI* (Comparison between 'Route', 'Aggregated' and 'Average' Methods)



In general, the results from 'aggregated' and 'average' methods confirm that general validity of the estimate from the 'route' method. The results from the two later methods do not provide a convincing case for revising the parameters derived from the results based on 'route' analysis. The recommendation therefore is to adopt the 'route' parameters and to use them in further analysis and application.

5.2 Comparison with Findings from Leeds and London

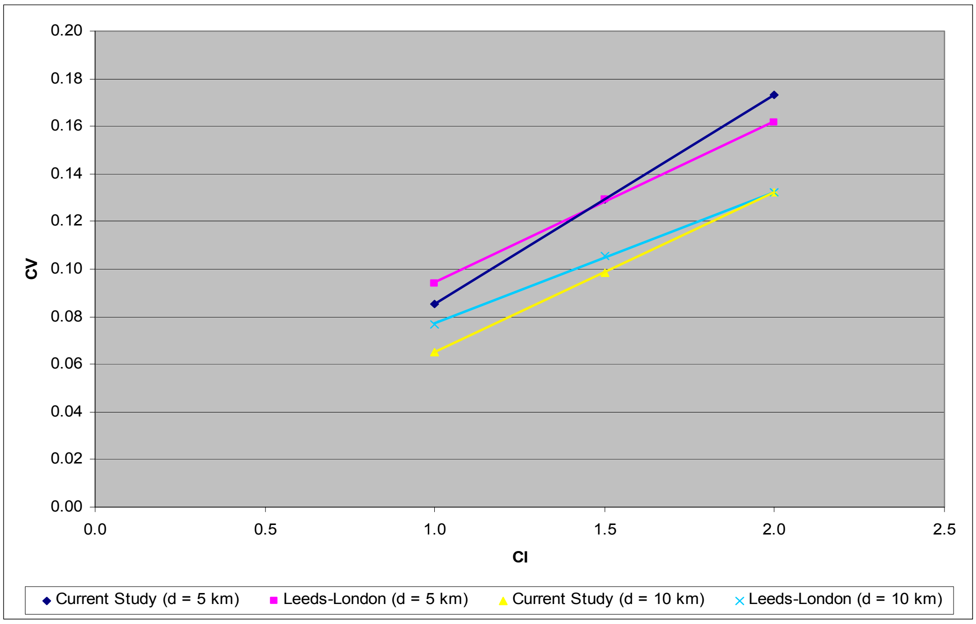
Table 6 compares the coefficients recommended in the previous section with those previously obtained using the Leeds and London data. The coefficients estimated in the current study are all higher than those from the Leeds-London study (*d* elasticity is higher in the negative term).

Table 6 Coefficients of Current and Previous Studies

Coefficient	Current Study	Leeds-London
α	0.16	0.15
β	1.02	0.78
δ	-0.39	-0.29

Figure 7 shows the *CV*s calculated using coefficients from Table 6 above for *CI* = 1.0, 1.5 and 2.0, and *d* of 5 km and 10 km. It is clear that the current study has a steeper slope than the previous study. This means the *CV* increases with *CI* and is more sensitive in the current study compared to Leeds-London study.

Figure 7 *CV* against *CI* (Comparison between Current and Previous Studies)



6 SLA and MLA Findings for the Holiday Period

The analyses carried out using 'Holiday Period' data suggest that the model coefficients for this period are not significantly different to those derived in the main analysis for neutral months. Differences in *CV* between these periods are therefore accounted for by differences in their *CI* values.

7 Model Application and Economic Appraisal

Demonstration schemes for which appropriate Transport Analysis Guidance Website (WebTAG) compliant models and appraisals were available were identified in Bath and Nottingham. The Bath scheme comprised a notional link road while the Nottingham scheme comprised junction and link capacity improvements. The consultants responsible for these studies provided appropriate data for input to TTV appraisal.

A methodology was developed to produce travel time *CV* and scheme monetary benefits which are consistent with Transport Users Benefit Appraisal (TUBA) economic appraisal. This was implemented for both schemes using database and spreadsheet applications.

The two example applications are representative of major urban schemes which would be appraised using WebTAG compliant multi-modal models. They cover areas with differing characteristics, with Bath having a road network comprising traditional urban roads with strong frontage interaction, while Nottingham has some more modern segregated roads, particularly the ring road.

The Bath application showed that it is possible for trip matrix cells with outlier *CI* values to significantly distort the estimated benefits. Such outliers might be caused by network coding errors or unreasonable model responses. To ameliorate this problem a 'capping' process has been implemented which ensures that all *CI* are in the range between 1 and 20. This resolved the problem for Bath and had no significant impact for Nottingham.

For Bath the AM Peak TTV to travel time benefit ratio for all trips was 22% while for Nottingham it was 26%. For the Inter-Peak the TTV to travel time benefit ratio was 11% for Bath and 15% for Nottingham. The consistency of these results demonstrates that the TTV appraisal methodology is robust in the context of the different urban areas and scheme types tested.

These results also demonstrate that TTV benefits form a significant element of overall benefit and that this should be taken into account in urban scheme appraisal. TTV benefits are more important in the Peak than Inter-Peak periods. This suggests that TTV benefits increase as congestion increases. TTV benefits will therefore be particularly important in highly congested areas such as the inner city areas of major conurbations.

8 Conclusions

This research has confirmed that ITIS/CJAMS data can successfully be used to study TTV. In the case of single links the process generates more than adequate sample sizes suitable for robust estimates of *CV* and analysis. However when carrying out MLA for some route and time period combinations, the database did not generate sufficient size samples to allow good estimates of TTV. Analysis of journeys above 10 km was severely limited with only seven journeys being generated from the dataset as a whole.

The data collected for 34 routes allowed useful analysis at the single link level. The *CI* elasticity estimated for each of the links in the 34 routes ranges from -0.5 to 6.5. The good quality of the data providing distinctive patterns of *CV*-*CI* on different links suggests that analysis of the causes behind the differences between links would be a profitable exercise with this data set.

In order to understand how *CV* varies with journey length, the MLA constructed for each route contains four series of *CV*, *CI* and *d* (in 30 minute timeslots between 07:00 and 20:00) – a series representing average single link data and three series representing multi link journeys along the route in question. Analysis of this data allowed a journey elasticity formula to be developed for each route. The average relationship found was:

$$CV_t = 0.16 CI_t^{1.02} d^{-0.39} \tag{6}$$

where CV_t = Coefficient of Variation in timeslot *t*
CI_t = Congestion Index in timeslot *t*
d = Distance (in kilometres)

and $CI_t = \frac{t}{T}$

where t = Travel Time
T = Reference Travel Time

The general scale of these parameters was confirmed by two alternative methods of analysis, namely ‘aggregated’ and ‘average’.

In predicting *CV* at *CI* levels of 1 and 2 the variation between routes is ±27% and ±31% respectively. This 95% confidence interval represents the error range to be expected if an average relationship is used rather than an individual relationship.

If the average relationship reported above is compared with the average of the Leeds and London studies ($CV = 0.15\ CI^{0.78}\ d^{-0.29}$), the constant term is similar, whereas the *CI* elasticity and the *d* elasticity (negative) are both higher.

The findings from the current study are preferred to the original Leeds-London estimates for two reasons. Firstly the data collected in the London study was only for the period between 07:10 and 07:50, and hence the relationship estimated was based on this period only. Secondly the sample sizes in the previous studies were limited. For instance, the sample size in the Leeds study was only 10 records for each timeslot.

An important difference between the previous Leeds and London studies and the current study is that both of the earlier studies were based on data collected using the moving observer method over a short timespan of less than a month. Given this study incorporates data over three years and all seasons it might have been expected that the estimates of *CV* would have been higher than those from the earlier method. This is not the case, as can be seen in the comparison of the *CV*s calculated using coefficients from the current and the previous studies.

The findings from the analyses carried out using data observed during the holiday period are not significantly different to those obtained from the main analysis.

The two demonstration applications are representative of major urban schemes which would be appraised using WebTAG compliant multi-modal models. They cover areas with differing characteristics, with Bath having a road network comprising traditional urban roads with strong frontage interaction, while Nottingham has some more modern segregated roads, particularly the ring road. The schemes appraised vary from a link road in Bath to junction and link capacity improvements in Nottingham.

This stage of the study has specified how the appraisal of TTV benefits can be included in urban traffic appraisal. The required inputs to the appraisal have been successfully extracted for the studies by two separate consultancies. This demonstrates that the required inputs can be produced by typical urban multi-model or highway network models. These inputs have been used to estimate TTV benefits in a consistent manor to TUBA travel time benefits. These results also demonstrate that TTV benefits form a significant element of overall benefit and that this should be taken into account in urban scheme appraisal. TTV benefits are more important in the Peak than Inter-Peak periods.

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Note

The work described in this paper was carried out by Hyder Consulting, in collaboration with Ian Black and John Fearon, under contract to the UK Department for Transport. However, the views expressed are those of the authors and are not necessarily the views of the UK Department for Transport.