ORIGIN-DESTINATION MATRIX ESTIMATION FOR THE ACTIVE TRAFFIC MANAGEMENT PROJECT

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INTRODUCTION

The Highways Agency (HA) is developing the concept of Active Traffic Management (ATM) schemes which will coordinate operational regimes such as controlled use of the hard shoulder as a running lane, variable speed limits and ramp metering. The pilot ATM scheme is planned to be implemented on the eastern section of the M42 between Junctions 3a and 7 by 2006. To ensure the success of all these measures, and to enable the network to be managed safely and effectively, knowledge of the behaviour of the traffic on the network is vital.

The HA’s practical requirement can be interpreted as:

- Real-time local estimation of entry-to-exit flows in fine time slices, with little or no route choice;
- Diversion strategies covering a larger area with alternative routes and fine time slices;
- Long term policies covering an even larger area but with coarse time resolution.

Origin-destination (OD) demand matrices are at the core of this information, but direct monitoring of trips is at present expensive and unreliable. The principal data sources available to traffic management systems remain inductive loops, which will provide dense coverage on the ATM section with 100m spacing, as compared with 500m spacing on the M25. The new and enhanced methods of dynamic origin-destination matrix estimation (ODME) developed in this project are designed to exploit this and to support the sophisticated real-time control systems on the section.

This paper describes the methods and results of the project conducted in three phases:

In Phase 1 several ODME methods were developed and tested by four contractors: TRL Limited, Mott MacDonald, University of Western Australia (UWA), and Modelit (formerly with Delft University). Methods can be divided into two categories: ‘Derivers’ which estimate an OD matrix from counts alone, and ‘Optimisers’ requiring a prior OD matrix which is then adjusted using counts. Reliable prior OD matrices are normally difficult to obtain and maintain. The thrust of the project is to develop a combined system, where a Deriver uses detector counts to estimate all or some of the prior matrix elements for an Optimiser, which is able to take into account route choice, including over a larger network which could extend to an entire Region. Quite extensive testing of the individual methods was conducted by their respective authors at this stage, not limited to the M42.

In Phase 2 the methods were evaluated by independent experts. Following a Round Table discussion, a selection was made to carry forward to implementation. UWA’s method (Maher and Zhang (2)) was not selected in this case. Modelit’s DeltOD method (van der Zijpp (4)) was chosen as the Deriver, and it was decided to combine the best features of the two Optimiser methods, both of which are based on dynamic Entropy Maximisation (see Hazelton & Gordon (1), Maher and Zhang (2)).

In Phase 3 the software enhancements have been made and the software tested using recent data from the M42. Route choice is not an issue on the M42 ATM section itself. Data collection on the M42 is not so long established and reliable as that on the M25 Controlled Motorway. The September 2002 MIDAS1 M42 loop data were judged to be the best available for the study but are still on the margins of what are required for reliable estimation. Figure 1 sketches the M42 count sites available to the study in each direction. However, the M42 will ultimately provide one of the richest sources of motorway traffic data anywhere.

Testing OD matrix estimation methods on real life applications is difficult. While methods may perform well on simulated data, vital as a first step in proving the method, the real test will be whether they can reproduce observed OD movements. These may be obtained from roadside surveys or from Automatic Number Plate Reading (ANPR) camera data once they become available with sufficient coverage. In Phase 3 of the current project, the results are being compared with data based on a manual OD survey conducted by Jacobs Consultants in September 20012. However, the limited number of days of loop data and the variation between them, as well as the gap of one year with the MIDAS data, makes it difficult to assess the quality of the results at this stage.

THE ODME PROBLEM

The fundamental limitation of OD estimation is under-specification, where there are fewer independent data than variables to be estimated, resulting in a non-unique solution. The approach DeltOD uses to

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1 Highways Agency’s Motorway Incident Detection and Automatic Signalling system.
2 The manual Survey covered AM peak, inter-peak and PM peak periods, but at a limited number of entry slips (J4-J6). An improved matrix for the period 0800-0900 only was produced by Mott MacDonald by adding through traffic from vehicle registration matching. Furnessing to automatic counts using tools in the SATURN assignment model suite, and finally cordonning and converting to a zone structure taken from a VISSIM model of the M42 ATM section.
overcome this is to exploit the statistical variability of traffic flow over many similar days, together with journey time information derived from detector speed measurements, to build up an average 'split' distribution matrix, which is the average proportion of each entry or origin flow allocated to each exit or destination available to it. The splits are assumed to vary less than the absolute origin flows. Time-dependent OD matrices can then be estimated by multiplying the split matrix by the origin flows. A disadvantage lies in the inherent smoothing of the data which limits the ability of a Deriver to track short-term changes in the real OD splits, although variations in the origin flows can be followed faithfully, and the overall traffic levels are preserved.

An Optimiser overcomes under-specification by starting with a prior matrix and using a technique such as Entropy Maximisation to select the estimate which is most consistent with the counts and the prior matrix, so the prior matrix makes up the information missing from the counts. In the selected method, whose standard version is implemented in the CONTRAM traffic assignment suite (Taylor (3); www.contram.com), the respective levels of ‘belief’ in the prior OD data and the counts can be adjusted independently for each OD cell and link count. Route information is derived from the OD demands by a dynamic assignment model, in this case CONTRAM.

The extended Optimiser developed in this project applies an enhanced version of the Method of Successive Averages (MSA) smoothing algorithm simultaneously to both the OD matrix and the assignment in order to improve convergence. In the future the user-friendliness may be further improved by integrating the components more closely. At present MIDAS and the ODME programs are interfaced by a number of special data conversion programs, but in time they could be integrated within a single user-friendly shell. DelftOD may be extended to allow route choice, based on proportions estimated by a dynamic assignment model such as CONTRAM, while day-to-day repeat observations may be used by the Optimiser to reduce underspecification. The modelling engines will, however, remain separate, and detailed descriptions of them will be published separately in the form of technical reports and manuals.

THE DELFTOD SUITE

The DelftOD software was first developed while its author was working at Delft University, but ownership, development and marketing are now through the consultancy Modelit (www.modelit.nl). It consists of a package of MatLab routines which have to be executed in a particular sequence to process the data through several stages: data cleaning and other checks, OD split estimation, optional estimated/observed flow comparison, and OD matrix generation. In its present form, DelftOD requires a unidirectional network without route choice.

In Phase 1, experiments using simulated data on the controlled section of the M25, generated by TRL/HA’s SISTM microscopic model, showed that in theory high accuracy can be achieved. Tests using real data were also done using five essentially linear corridors in the network of Kent, based on an existing CONTRAM data set (see Figure 2), though in this case no ‘true’ OD matrix was available for comparison.

DelftOD requires a set of network definition files to specify node coordinates, link definitions (the nodes they join and their actual length) and loop positions (link where located and distance from upstream end). Certain nodes are identified as origins or destinations. Where speed data are available, DelftOD adjusts time-mean speeds to space-mean, and uses an algorithm to recreate sample journeys. These journeys allow counted flows to be projected through the network and compared with other counts or used to estimate flows on uncounted links.

An essential process in DelftOD is ‘data cleaning’. This is partly a manual process of selecting days and periods which are free from anomalies such as incidents, and specifying consistency ‘equations’ between sets of inflows and sets of outflows, and partly an automated process whereby counts are adjusted or filled in, working in the downstream direction, so that a complete mutually consistent set of origin and destination flows is made available.

Another feature of DelftOD is aggregation or ‘synchronization’ of data. Figure 3 shows how different aggregations can be used at different stages of the estimation. MIDAS data are provided in 1 minute periods, but this can result in too much variability for reliable split estimation, so 5 minute aggregation is recommended. However, this does not mean that either the splits or the OD matrices have to be estimated at this resolution. In fact the data in the M42 case would not support estimation of splits to finer resolution than a period of several hours such as the AM peak. On the other hand, the resolution required in the ODs is determined by the needs of the Optimiser or an incident management tool such as MOLA3. The former might require hourly average flows, while the latter requires 5 minute periods to be estimated. In Figure 3, the middle (green) areas represent the range of aggregations considered ‘safe’.

Once the data have been cleaned, OD estimation can take place. This is done using a Bayesian approach where numerically possible, with Maximum Likelihood as the fall-back. Underlying this is the correlation between entry and exit flows implied by a

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3 Motorway On-Line Assistant is a Windows package for developing and setting Variable Message Sign strategies which uses the assignment program MCONTRM or CONTRAM (v. 8+) as its engine.
fixed split matrix which is assumed to apply not only during a certain period of the day but also on a number of successive days. Vectors of entry flows which are assumed to be samples from the same underlying distribution build up a picture of the hypothesised underlying split pattern. The program issues a report giving the means and standard errors of the splits for those OD pairs which are connected, and reaches a conclusion as to whether the computation of the mean split matrix or matrices has been successful. One possible failure mode is for a mean to come out negative with a small standard error (ie with apparent significance), while a small negative mean with a large standard error may be considered equivalent to a zero.

DELFTOD ON THE M42

In the case of the M42 networks, some loops (underlined in Figure 1) were partly or completely non-functional in September 2002, and 15 weekdays were considered usable, enabling the data to be divided into two sets, one for testing and one control. Using the September 2002 MIDAS data, care had to be exercised in the choice of periods within the day, in particular the AM peak. The greatest difficulty was experienced at the onset of the peak. With hindsight this is not surprising since this is when flows change more rapidly than at any other time of the day, and it may be expected that the split matrix (ie the trip pattern) changes rapidly also. So an ‘average’ split matrix encompassing the whole morning peak may not be reliable. In practice, each direction was divided independently into five periods spanning 0530 to 2130: early morning, AM peak, inter-peak, PM peak and early evening; with one split average matrix estimated for each period. These were then exported as average OD matrices by factoring the origin flows.

DAY TO DAY VARIATION

For testing with the Optimiser, matrices for south- and north-bound AM, inter-peak and PM periods, corresponding to the original Survey periods, and one-hour matrices corresponding to the improved 0800-0900 Survey matrix were created. For MOLA experiments, 5 minute OD matrices have been generated. There is considerable scatter at the 5 minute level, as shown by Figure 4 which samples the estimated Southbound 0530-2130 matrix between two major slips near Junction 3. This mainly reflects the variability in the actual origin flows. The AM and PM peaks are clearly visible, as is the steep onset of the AM peak. It is not obvious where the ‘joins’ between the five split averaging periods occur (in fact they are at 0700, 1100, 1600 and 2000).

To get a feel for day-to-day variation, DelftOD was run with data from 13 individual days for the central AM peak period 0700-1000 (2 days being excluded because a solution could not be achieved). Combining the means and standard errors of individual days gave the range of splits shown in Figure 5, where separate OD movements are arranged along the horizontal axis in arbitrary order, the standard error range of split estimates is shown by the bars, and the circles represent the improved Survey matrix split values. Where a mean is below the zero line, the estimations have mostly been unsuccessful, and the split value would usually be replaced by zero.

The results show that there is considerable uncertainty in the splits, due partly to uncertainty of estimation and partly to day-to-day variation. At the same time the improved Survey splits are broadly consistent with the estimated ranges. Any variability due to day-to-day variation in total origin flows will generally be additional to this, although certain splits may dominate the flows. Hence it may be difficult to establish a match between a matrix estimated using many days’ data for an average day or one type of day, and one observed on a specific, supposedly similar day.

CONTRAM MATRIX ESTIMATION

Given a prior OD matrix and a set of link traffic counts, ‘Optimiser’ matrix estimation aims to produce a new demand matrix where the modelled link flows are as close as possible to the observed count data, subject to the constraint represented by the prior matrix. An Optimiser is less dependent on historical data than a Deriver, and so can potentially overcome the latter’s susceptibility to day-to-day variation. However, it is often applied to updating an old and/or manually adjusted matrix using more recent counts, in order to achieve a better match to reality. The constraint may be expressed in terms of maximising the relative entropy between the estimated and prior matrices, so that the estimate is the least ‘special’ one which satisfies the counts. In capacity-restrained networks, a change in the OD matrix is likely to lead to changes in routes, affecting the modelled flows which are to be compared with the counts. Therefore, it is standard practice to iterate matrix estimation with assignment, until a stable result is achieved.

CONTRAM ME includes the following features:

- Weight on both counts and matrix elements
- Link counts and turning counts
- Classified and unclassified counts
- User-defined time slices
- Counts on screenlines and groups of links
- Counts by time slice, or aggregations thereof
- Automated assignment-estimation iteration

The completely flexible way in which weights can be applied to individual matrix elements and counts is thought to be unique to CONTRAM, and enables users to reflect their perception of the reliability of the data.
ORIGINAL MATRIX ESTIMATION METHOD

Mathematical definitions
The method developed and coded by Mott MacDonald in mathematical terms is as follows. Given:

- \( t_{ijct} \) the number of trips from \( i \) to \( j \) of class \( c \), departing in time slice \( t \) in the Prior matrix
- \( x_{ask} \) the modelled flow on link \( a \) in count period \( s \) class \( k \)
- \( v_{ask} \) the observed count on link \( a \) in count period \( s \) class \( k \)
- \( w_{ask} \) the weight (level of confidence) for the count on link \( a \) in count period \( s \), class \( k \)
- \( \mu_{ijct} \) the weight associated with \( t_{ijct} \)

the method calculates:

- \( V_{as} \) the target flow on link \( a \) in count period \( s \), class \( k \)
- \( T_{ijct} \) the number of estimated trips from \( i \) to \( j \) of class \( c \), departing in time slice \( t \).

All variables except weights are expressed in veh/hr.

If \( t_{ijas}^{as} \) is the number of trips from \( i \) to \( j \) of class \( c \) departing in time slice \( t \), that pass through link \( a \) during count period \( s \), then the “pija” proportions are defined as follows (noting that the subscript \( k \) for count class is not required as the classes are mutually independent:

\[
p_{ijct}^{as} = \frac{t_{ijct}^{as}}{t_{ijct}}
\]

Formally, the problem is to minimise:

\[
Z = \sum_{s=1}^{S} \left( \sum_{ijct} \mu_{ijct} \left( T_{ijct} \ln \frac{T_{ijct}}{t_{ijct}} - T_{ijct} + t_{ijct} \right) \right)
+ \sum_{s=1}^{S} \left( \sum_{a \in A} \left( V_{as} \ln \frac{V_{as}}{v_{as}} - V_{as} + v_{as} \right) \right)
\]

subject to: \( V_{as} = \sum_{ijct} p_{ijct}^{as} T_{ijct} \)

The solution is an updated matrix and target flows on links calculated according to:

\[
T_{ijct} = t_{ijct} \prod_{a,s} X_{as}^{\frac{1}{w_{as}}}
\]

\[
V_{as} = v_{as} X_{as}^{\frac{1}{w_{as}}}
\]

where \( X_{as} \) is the balancing factor for link \( a \) in count period \( s \), which is calculated by the method.

Iterative procedure

Given:

- the network data file
- \( T^0 \), the demand matrix specified therein
- \( t \), the Prior matrix (may be equal to \( T^0 \))

the Matrix Estimation procedure is as follows:

1. If not already assigned, assign demand to the network using matrix \( T^0 \)
2. Set iteration counter \( N=0 \)
3. Run the basic ME procedure, using the assignment of \( T^N \) to calculate “pija” factors, with \( t \) as the Prior matrix. Output revised matrix \( T^{N+1} \)
4. \( N=N+1 \). Go back to step 3 and repeat until a specified number of loops have been completed.

IMPROVED AVERAGING METHOD

TRL has recommended an improvement which essentially outputs a weighted average of the revised and original matrices at each step, and also calculates revised “pija” factors – in other words a revised loading of traffic – by similar averaging. The averaging process is essentially the Method of Successive Averages (MSA), in which the step length taken towards the revised estimate diminishes with each iteration. MSA is often chosen because of its reliable convergence, but the price can be slow convergence. Variations exist in which the step length can be accelerated or decelerated according to how well the algorithm appears to be converging. However, the critical issue with Matrix Estimation is the absolute level of convergence, and the new method should improve this, giving better estimates and overall convergence statistics.

The Averaging method can be summarised as follows:

1. If not already assigned, assign demand to the network using matrix \( T^0 \)
2. Set iteration counter \( N = 0 \)

3. Run the basic ME procedure, using the assignment of \( T^N \) to calculate “pija” factors. Call these \( Q^N \).

4. Calculate modified “pija” factors
\[
P^N = \left(1 - \frac{1}{N+1}\right)P^{N-1} + \frac{1}{N+1}Q^N
\]
and use these in subsequent estimation process with \( T \) as the Prior matrix. Output estimated matrix as \( U^{N+1} \).

5. Calculate a revised matrix
\[
T^{N+1} = \left(1 - \frac{1}{N+1}\right)T^N + \frac{1}{N+1}U^{N+1}
\]

6. \( N = N + 1 \). Go back to step 3 and repeat until a specified number of loops has been completed.

**CONTRAM ESTIMATION ON THE M42**

DelftOD and CONTRAM share a similar network data structure of nodes joined by links which carry all the network properties, but CONTRAM data are naturally much more complex. In this project the DelftOD network was created first, so utility programs have been created to convert OD matrices and basic network data from DelftOD to CONTRAM format. In the future, it would seem natural to convert networks in the other direction, which would reduce the amount of manual editing required. However, conversion of OD matrices will still proceed naturally from the Deriver to the Optimiser, leaving only the translation of zone numbers to be specified, if required.

CONTRAM OD matrices define each classified origin-destination movement as a time-sliced flow profile. The time-slices are chosen by the user and can vary through the period modelled. The utility conversion program, however, generates time slices of equal length. As mentioned before, for testing, a one-hour period has been extracted, but for some research connected with ATM, matrices covering 16 hours in 5 minute time slices are required. Corresponding files of observed counts can be obtained directly from the original MIDAS data using another utility program.

Alternative selections can be made very easily using the utility programs, and include the ability to select certain days, so that the data represent, for example, a typical Thursday or an average weekday as required. The selection facilities also make it easy to divide the data into an experimental set and a control set. In this case the first 7 days of the 15 ‘good’ days of counts available in September 2002 provided the prior matrices, leaving the remaining 8 days for creating the link counts to be used in the matrix estimation process.

Currently, DelftOD works only with unclassified vehicle flows, and additional processing would have been needed to take account of the MIDAS class information, which is separate from count and speed data. Therefore the DelftOD and CONTRAM matrices include vehicles of all types. The improved Survey matrices, which are divided between light and heavy vehicles, have been combined for the purposes of this work, divided between south- and northbound directions, and factored to match the total OD trips in the comparison matrices.

The testing of the Optimiser method has been carried out as follows and summarised by Figure 6:

1. Compare the prior matrix (from DelftOD) with the observed (improved Survey) matrix;
2. Run the Optimiser using a variety of combinations of weights on prior matrix elements and counts, comparing results with the prior matrix and input counts;
3. Compare the matrix resulting from (2) with the observed matrix; and
4. Check the results from (2) against results from ME tests with averaging switched off (that is using the original CONTRAM method).

Various statistics recommended by the DfT for comparing results include RAAD (Relative Average Absolute Difference), AAD (Average Absolute Difference) and RMS (Root Mean Square). These are used for comparing OD matrices. A useful statistic for comparing either matrices or link flows is the GEH, which embodies a degree of independence of scale:

\[
GEH = \sqrt{\frac{(M - C)^2}{(M + C)/2}}
\]

where \( M \) and \( C \) represent the modelled flow and the count respectively. A value of 5 or less is usually considered acceptable for this statistic and DMRB recommends that for validation a target of 85% of model flows should achieve a GEH of 5 or less.

Runs were carried out using different values of weights on link counts and on prior matrix cells, in order to determine the most satisfactory values. These include:

1. Increasing weights on counts by factor of 5, keeping weights on matrix cells fixed;
2. Increasing weights on matrix cells by factor of 5, keeping weights on counts fixed;
3. Increasing both sets of weights by factor of 5 at the same time, as a check that only the relative values of weights influence ME.

Applying a high ratio of prior matrix weights to count weights tends to move the estimated matrix closer to the prior matrix, in terms of the various statistics mentioned earlier, but has the opposite effect on the fit between the estimated and observed link counts. Figure 7 shows that by choosing the weights appropriately it is possible to get a good match to the link counts. However, despite a good overall match, some of the link flows differ significantly between the Prior (DelftOD) and Survey matrices. This is a consequence of differences in the trip distributions, since the total number of trips is the same in the two matrices.

Table 1 summarises the percentage of the link GEH values less than or equal 5 for each direction in each time slice over the whole set of matrix estimation runs carried out (240 values of GEH for each time slice).

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Southbound</th>
<th>Northbound</th>
</tr>
</thead>
<tbody>
<tr>
<td>07:00 – 08:00</td>
<td>91.6 %</td>
<td>-</td>
</tr>
<tr>
<td>08:00 – 09:00</td>
<td>100 %</td>
<td>-</td>
</tr>
<tr>
<td>09:00 – 10:00</td>
<td>97.5 %</td>
<td>93.3 %</td>
</tr>
<tr>
<td>10:00 – 11:00</td>
<td>82.5 %</td>
<td>85.8 %</td>
</tr>
<tr>
<td>11:00 – 12:00</td>
<td>87.5 %</td>
<td>87.5 %</td>
</tr>
<tr>
<td>12:00 – 13:00</td>
<td>100 %</td>
<td>95.0 %</td>
</tr>
<tr>
<td>13:00 – 14:00</td>
<td>98.3 %</td>
<td>95.0 %</td>
</tr>
<tr>
<td>14:00 – 15:00</td>
<td>100 %</td>
<td>86.2 %</td>
</tr>
<tr>
<td>15:00 – 16:00</td>
<td>77.9 %</td>
<td>71.6 %</td>
</tr>
<tr>
<td>16:00 – 17:00</td>
<td>90.8 %</td>
<td>87.1 %</td>
</tr>
<tr>
<td>17:00 – 18:00</td>
<td>88.7 %</td>
<td>84.6 %</td>
</tr>
<tr>
<td>18:00 – 19:00</td>
<td>100 %</td>
<td>95.0 %</td>
</tr>
<tr>
<td>19:00 – 20:00</td>
<td>88.7 %</td>
<td>78.7 %</td>
</tr>
</tbody>
</table>

As the table shows, all but one of the Southbound GEH tallies are above 80%. So a good match between counts and the modelled flows has been achieved, according to the 85% criterion. The match for the Northbound direction is also good. Given that the splits are fixed in each period, a perfect match cannot be expected.

Table 2: Prior v. Survey OD matrix statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>RAAD</td>
<td>78 %</td>
</tr>
<tr>
<td>AAD</td>
<td>168 [Veh Trips]</td>
</tr>
<tr>
<td>RMS</td>
<td>243 [Veh Trips]</td>
</tr>
</tbody>
</table>

However, the match between the OD matrices is poor, as shown by Table 2 (RAAD of 78% means that on average Prior matrix cells differ from corresponding Survey cells by 78% of their value). Reasons for this could include the effects of day-to-day variation as cited earlier, and it is not known how travel patterns may have changed between September 2001 and 2002.

**COMPARISON WITH SURVEY**

This comparison is at the core of testing ODME methods and is the final step in the evaluation of the quality of a new technique. However, its results can also be the most difficult to interpret, as so many factors are involved. As previously, the comparison has used RAAD, AAD and RMS statistics to compare estimated and Survey OD matrices, while the GEH statistic has been used to compare link flows.

The RAAD statistic comparing Prior and Estimated OD matrices (Figure 8) is minimum when the greatest weight is placed on the prior matrix at the expense of the counts, but indicates that even with maximum weight on counts the impact of matrix estimation on the OD matrix is small. The fraction of links with GEH less than or equal to 5 across all matrix estimation runs is only 48.3%. GEH values are also found to vary little between iterations of the ME procedure.

The RAAD statistic comparing Survey and Estimated OD matrices (Figure 9) reaches minimum value when the ratio of weights is 0.2 (5:1 in favour of link counts). However, the RAAD values are so high that it would be unwise to place much confidence in this value. Altering the weights on counts or matrix cells does not bring significant advantages in terms of matching the OD trips. The average value for RAAD is about the same as that found when comparing the Survey matrix with the Prior (Table 2), representing a poor match. This is not entirely surprising, as the ME process will try to match OD Prior matrix trips or counts. If there are already differences between the Survey and Prior matrices, then these will tend to persist between the Survey and Prior OD matrices.

**CONCLUSIONS**

The DelftOD Deriver method has proved capable of estimating OD matrices on simple network sections using repeated observations taken from a sufficient number of days, opening the way to continuous on-line estimation. However, it has not been possible to reach a conclusion about the reliability of its estimated matrices in comparison with the Survey matrices. Since the DelftOD method requires many days of data, it cannot be expected to match the real OD matrix on a daily basis, unless the trip pattern is very stable.

The results from the Optimiser method, including its enhancements, are inconclusive since the estimated matrices are not better matched to the surveyed matrices than to the prior matrices. The Averaging
method has not really been tested due to the lack of route choice, but the modified software reproduces earlier results correctly. The reasons for the inconclusive results appear to be threefold:

- Limited data from the M42 available at the time of the study;
- One year gap between the manual Survey and the MIDAS data used;
- Substantial day-to-day variation in OD splits.

To reach reliable conclusions about the validity of estimates, it may be necessary to conduct tests targeted at specific days, with fully surveyed comparison matrices (eg using Automatic Number Plate Recognition data). The potential of the combined matrix estimation system can be expected to improve as more detectors come on line on the ATM section.

ACKNOWLEDGEMENTS

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REFERENCES


Figure 1. Sketch of M42 (ATM section) showing inactive (underlined) and working loop sites in September 2002
Figure 2. Corridors in Kent network selected for DelftOD testing

Figure 3. Showing relationship of data aggregations at different stages of DelftOD

Figure 4. One OD movement on M42 estimated by DelftOD at 5 minute resolution

Figure 5. Ranges of DelftOD split estimates from 13 individual days of M42 data in Sep 2002. Circles = Survey values (main carriageway and slip at J3 combined)
Figure 6. Scheme of matrix estimation and comparison

Figure 7. Prior v. Survey – counted link flows comparison

Figure 8. Prior v. Estimated counted link flows – RAAD statistic as function of matrix/count weighting

Figure 9. Survey v. Estimated OD matrices – RAAD statistic as a function of matrix/count weighting