Practical Considerations in Implementing Travel Time Reliability in Regionwide Travel Forecasting

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ABSTRACT
Travel time reliability has been shown to influence travelers’ decisions as to choice of destination and choice of route. This paper explores options for the inclusion of travel time reliability into a regional travel forecasting model and tests those options on a full-sized network in the Wheeling metropolitan area. Options include two different path building algorithms, different parameters (locally derived v. borrowed) for the coefficient of variation of link travel time, and the size of the “reliability ratio”, which is the weight for the standard deviation of travel time when included in the path impedance function. The two path building algorithms were the “naïve” algorithm, which does not find shortest paths but weights reliability the same on each link, and the “shortest marginal” algorithm, which does find shortest paths but emphasizes variations in delays on links earliest in a path. The tests are not considered definitive due to relatively low congestion levels in Wheeling, but there were indications that the “naïve” algorithm and borrowed parameters performed best. The experience showed that including travel time reliability in regionwide travel forecasts is straight-forward, there are ample resources to establish reasonable parameters, no compromises need to be made for implementation, and that the computational burden is modest. However, it is important that any model have very good travel time and delay estimates to begin with before layering on reliability as another consideration for path selection.

Keywords: Travel Demand Modeling, Reliability, Dynamic Assignment
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INTRODUCTION
The reliability of travel time has become an important consideration in the evaluation of intelligent transportation systems, but it has only recently caught the interest of planners who develop traffic forecasts and long-range transportation plans. The inclusion of travel time reliability in such forecasts has certain challenges, both theoretical and practical, that must be addressed in some manner, as there exist both knowledge gaps and incompatibilities with common professional practice. This research explores alternative strategies for modeling travel time reliability and compares those strategies on a travel forecasting network for the Wheeling metropolitan area, deemed to be small enough to serve as a good test case, but also large enough to have results that identify some areas of concern for larger metropolitan areas.

There have been proposed a number of measures of travel time variability, including buffer index and planning time index \( (1) \), and coefficient of variation of travel times and travel time index \( (2) \). Many of these measures were created for public consumption. The most often considered measure of reliability for use within traffic models is simple standard deviation of travel time, perhaps because of the similarity of units between this statistic and path impedance (aka disutility), which often also has units of time. Conceivably, an enhanced path impedance can be obtained as a linear combination of standard deviation of travel time, mean travel time and other factors. Studies investigating the value of the standard deviation of travel time have determined that one unit of standard deviation is worth between roughly 0.5 and 1 units of mean travel time \( (3,4) \), but varying considerably from study to study.

It is well known that bread-and-butter path building algorithms found in travel forecasting models based on Dijkstra’s classical method \( (5) \) cannot guarantee finding the shortest path when the impedance function contains a term with a standard deviation. This fact has been cited by multiple authors (see reviews by Zhou \( (6) \) and Gao \( (7) \)), as a rationale for developing new algorithms that have a better chance of finding a shortest path, although there does not exist a consensus (to our knowledge) as to whether drivers consistently choose shortest paths during actual driving under uncertain conditions. Maintaining a shortest-path paradigm within planning models that consider reliability has considerable costs, both in software development time and computational resources, so it would seem prudent to try to ascertain whether shortest paths are selected by drivers in the real world or even if it makes much difference in forecasts.

For any street or intersection there exist many reasons why travel times are uncertain. Travel times can vary because of minute-to-minute changes in traffic demand or vehicle mix, adaptive intersection traffic controls, unexpected events such as bad weather or incidents, unusual traffic maneuvers or dumb luck. For some simple situations, such as a fixed-timed signal \( (8,9) \), it is possible to derive an equation of the standard deviation of delay. However, the broad range of
possibilities would suggest that an empirical relation for standard deviation of travel time, such as the one proposed by Black, Fearon and Gilliam (10,11) might work best within travel forecasting models. Regardless of the chosen relation, it is important to eliminate as many sources of variation as possible, such as diurnal demand variations, by constraining the analysis to a very short time period, statically, or performing a dynamic traffic assignment (DTA). Ideally, the time period (or time slice) of the simulation would be similar to the length of time a driver would consider the traffic system to be reasonably stable.

This research tests two different relations for travel time and two different path building algorithms on a DTA-based travel forecasting model. Comparisons are also made with existing travel times and volumes. Finally, instances where simplifications could be made and a role for additional research are discussed.

It should be noted that while the procedures described in this paper can work with model networks that do not directly include intersection controls, it is much preferred that these procedures be used in conjunction with such controls – and the MPO case study in this paper fully incorporates such controls.

RELATIONS OF TRAVEL TIME VARIATION
The test model was created using a specially modified version of QRS II. Both link and node approach delays are included in path building. Conceivably path impedance, in units of minutes, could embody any of these items, in addition to the standard deviation of travel time:

Link impedance elements
  a. Uninterrupted link traversal time  
  b. Link monetary cost  
  c. Link distance  
  d. Unusual link deterrence to travel  

Node approach impedance elements
  e. Signalized intersection delay  
  f. Two-way stop delay  
  g. All-way stop delay  
  h. Roundabout delay  
  i. Ramp meter delay  
  j. Turn penalties (fixed or variable)

Aspects of travel that only advance the clock (in DTA) but cause no delay are not directly considered in path building. Only elements a and e through i are assumed to be subject to variability.
Black, Fearon and Gilliam proposed the following relationship for the coefficient of variation of travel time, $CV$:

$$CV = \gamma \left( \frac{t}{t_0} \right)^{\delta} L^\phi$$  \hspace{1cm} (1)$$

where $t$ is the loaded travel time, $t_0$ is the free travel time, $L$ is the length of the link in either miles or kilometers. The other variables are calibrated parameters.

It is important to recognize that average delays at intersection approaches are not zero when traffic is negligible, so it is necessary to estimate free travel time for each node’s approach as well as for each link. In addition, free travel time at signalized intersections depends on signal timing and signal timing depends upon traffic volumes (of which there are theoretically none under “free” conditions). Thus, free travel times at signalized intersections must be estimated using the volumes that would exist if the network had been loaded with traffic. For the sake of simplicity, a node’s approach delay is combined with the travel time of the corresponding link.

There are many possible definitions of path impedance. However, there is a growing body of empirical work to support a definition of path impedance as the sum of all link and node approach impedances and a path variation term. The path variation term is a constant, identified as $RR$ (reliability ratio) by Small, Winston, Yan (3) and others, multiplied by the standard deviation of the path travel time. Thus:

$$I_{\text{path}} = RR \sigma_{\text{path}} + t_{\text{path}} + y_{\text{path}}$$  \hspace{1cm} (2)$$

where $I_{\text{path}}$ is the total impedance including reliability, $y_{\text{path}}$ is the sum of the non-time impedance components in units of time, and

$$\sigma_{\text{path}}^2 = \sum_{i=1}^{M} \sigma_i^2 + \sum_{i=1}^{M-1} 2 r_{i,i+1} \sigma_i \sigma_{i+1}$$  \hspace{1cm} (3)$$

where $i$ is the link on the path consisting of $M$ links ordered from origin to destination, $\sigma_i$ is the standard deviation of travel time on link $i$, and $r_{i,i+1}$ is the correlation between adjacent links \hspace{1cm} (10). $\sigma_i$ is determined from Equation 1 by multiplying $CV$ by $t$, link travel time. Black’s et al. method of calculating path standard deviation ignores correlations between nonadjacent links, which are likely small in any event. We have retained this assumption in our work, but have also eliminated correlations between adjacent links that are separated by a turn at a traffic controlled intersection, thus emphasizing those link pairings that share common features at intersections such as signal timing and coordination. Including the correlation between adjacent links is not difficult in a Dijkstra-like algorithm, and omitting the correlation altogether would introduce a
substantial imprecision in the calculation of path standard deviation. Correlations act as turn penalties, so the path building algorithm must be capable of handling turn penalties well.

It is worth pointing out that Equation 2 differs considerably in philosophy from path building criteria for many papers in the published literature in which the objective is to find the minimum time path under uncertain conditions, such as might be required for an in-vehicle navigation system. Instead, in Equation 2 uncertainty always increases path impedance and serves as a penalty on travel time, consistent with studies of drivers’ opinions. The shortest paths from Equation 2 will not be the shortest expected time paths, the most reliable path or some similar measure. The problem is deterministic with nonadditive link costs (11), which can be a difficult class of problem to precisely solve on large networks.

PATH BUILDING MODELS
Numerous path building algorithms have been proposed in the literature to find shortest paths when there is uncertainty. See recent doctoral dissertations by Zhou (6) and Gao (7) for reviews of work on this subject. When evaluating path building algorithms it is important to be cognizant of the anticipated worse case level of complexity of a travel forecasting model. Travel forecasting models may already involve many time slices within a DTA, multiple vehicle classes, multiple paths between origins and destinations, turn penalties and rigorous equilibrium convergence requirements. Even with parallel-processing, computation times can be long. Thus, efficiency is essential for any additions to a travel forecasting model.

We explore two possible path building algorithms, “naïve” and “shortest marginal.”

The “naïve” algorithm finds paths in a Dijkstra-like way where each link’s individual impedance is the weighted sum of travel times, link standard deviation and non-time components. The path impedance \( I_{\text{path}} \) by this algorithm will be considerably overestimated (as compared to Equation 2 and 3), and it is unlikely that shortest paths will be consistently found on congested networks. However, the amount of error in each path’s impedance can be tracked, so it is possible to remove this error before passing the path impedance on to trip distribution and subsequent steps.

We are not entirely prejudiced against the “naïve” algorithm because it mimics a behavior where drivers make decisions en route as to which link to choose at each intersection.

The “shortest marginal” algorithm attempts to find the shortest path between an origin and a destination, considering reliability, per Equation 2. The “shortest marginal” algorithm is offered as a heuristic at this time, although it has been subjected to considerable testing and has provided consistently good results. The “shortest marginal” algorithm replaces the standard deviation of travel time on each link with a “link-in-path reliability” component, which is taken to be the marginal increase in path standard deviation should that link be chosen next in the path. So if \( R_k \) is this “link-in-path reliability” for link \( k \), then
once this link has been chosen. Then for any known path, shortest or otherwise:

\[ \sigma_{\text{path}} = \sum_{i=1}^{M} R_i \]  \hspace{1cm} (5)

A considerable drawback to using Equations 4 and 5 is that \( R_k \) is dependent on the exact sequence of links in the path, so we would need to know the shortest path to correctly compute \( R_k \) for each link in the shortest path. This suggests that the problem can be solved using the method of successive approximations coupled with Dijkstra’s algorithm as a special case of dynamic programming \((13)\). The values of \( R_k \) and the sequence of links may be found by iteration, following these steps:

Step 1. Compute for all links in the network \( R_j^1 = \sigma_j \). Set the iteration counter \( N = 1 \).

Step 2. Find shortest paths with a Dijkstra-like algorithm using the set of link-in-path reliability values for iteration \( N \), \( R_j^N \). Compute \( \sigma_{\text{path}}^N \) from Equation 3.

Step 3. Increment the iteration counter, \( N \). Find new link-in-path reliability for all links in the network, \( R_j^N \), from Equation 4. Compute the amount of path error by:

\[ \text{path error} = \sum_{i=1}^{M} R_i^N - \sigma_{\text{path}}^{N-1} \]  \hspace{1cm} (6)

If the path error is zero or maximum iterations have been reached, then stop. Otherwise, go to Step 2.

This algorithm will converge exactly in a finite number of iterations, if it will converge at all. We have not observed a failure to converge in tens of millions of paths on large-scale networks of varying complexity and varying values of \( RR \). The number of iterations required for convergence seems to depend on \( RR \), with very large values of \( RR \) (e.g., 5) requiring as many as 10 iterations. With more reasonable values of \( RR \) (e.g., 0.5) convergence is quick.

Both algorithms were implemented in an experimental version of QRS II. QRS II uses a vine-building method for shortest paths, which was considered necessary given that path impedance for the “shortest marginal” algorithm was dependent upon whether the path turned at a traffic-controlled intersection. A vine, like a skim tree, consists of shortest paths from one origin to all destinations.
Equation 4 suggests that such shortest paths will place the greatest emphasis on variability early in the path. Travel time variability in links near the end of long paths will have little impact on path selection, as the values of $R_k$ tend to decline as $k$ gets closer to $M$. This notion is reinforced, intuitively, by noting that for those origin/destination pairings with more than one travel path, the further one gets from the origin point the fewer the options remain to get to the destination. Counterintuitively, the path from A to B is not necessarily the exact reverse of the path from B to A, even when the travel times in each direction are the same.

**Illustrative Numerical Example**
Figure 1 shows a small network, where each link impedance is given as a random number, in the form of mean $\pm$ standard deviation. Note that the impedances on links A, B, C and D are identical (1$\pm$1). For simplicity, the reliability ratio has been chosen to be 1.0 and there is no correlation between links. The exact solution can be found by inspection, with the shortest path following a straight line through links A, B, C and D. A comparison of path impedances to each node from the origin reveals that the incremental amount of new path impedance becomes smaller across each link as the path gets closer to the destination. The naïve algorithm fails to find the shortest path. The naïve path follows links E, C and D. The “shortest marginal” algorithm finds shortest paths by successively approximating a new set of link impedances, all of which are deterministic. Those links impedances are shown at the lower left of Figure 1. It is easy to see that those new link impedances will allow finding the exact solution by any convenient algorithm, once they are ascertained.
FIGURE 1 Illustration of the Naïve and Shortest Marginal Algorithms
WHEELING TEST CASE
The 3-county Wheeling metropolitan area (population 150,000) is located in the Ohio River valley 50 miles southwest of Pittsburgh. Their travel demand model is an iterative four-step process incorporating deterministic DTA (dynamic traffic assignment) regionwide at 60-minute intervals over a full day. As with other QRS II-based models, traffic assignment uses the method of successive averages (MSA) with feedback to distribution after each iteration of assignment. The network, adapted from the U.S. Geological Survey’s DLG roadway shapefile, contains roughly 300 zones, 5500 links, and 950 modeled intersections (125 signalized). Except for the addition of DTA, model procedures generally follow those previously developed for the Cedar Rapids model in the 1990’s (14,15).

As shown in Figures 2 and 4, this model – with or without reliability-based specifications - validates better than most for both daily traffic counts and local peak period travel time surveys conducted by the Wheeling metropolitan planning organization (MPO) staff (16). These surveys, however, while geographically extensive (Figure 3), have to date not been conducted with sufficient sample sizes to calibrate parameters related to reliability of the travel times. Therefore, surveys done by the staff of the neighboring MPO in the Parkersburg/Marietta region (roughly the same size urban area and congestion levels) were also utilized for this task, focusing on a smaller number of urban street corridors with larger sample sizes (17). Based on past experience with networks incorporating intersection controls, some means have always been needed (even if applied ad hoc) to provide a pre-assignment penalty where large intersection delays could occur, so that such delays do not unduly distort successive assignment iterations – particularly at unsignalized intersections, where oversaturated conditions can quickly escalate into unreasonably large travel times. An “off-line” link penalty option, utilizing the Parkersburg-area data, was considered the first step up from this ad hoc and reactive process toward a more systematic approach before the arrival of the software procedure described in this paper.

FIGURE 2 Regional Model Validation Figures by Test Option
NOTE: RRx = reliability ratio (*0.1), UKx = CV equation coefficients from UK study (9), WWx = coefficients from WWW (Parkersburg MPO) study (16), x = type of path-building (n = naïve, sm = shortest marginal). See References 19 and 20 for Validation Target and Sampling Error (Traffic Counts).

**FIGURE 3** Wheeling MPO’s Travel Time Survey Locations

**FIGURE 4** Average Travel Time Error on Urban Street Corridors (14, 21-25)
TEST OF TRAVEL TIME VARIATION RELATIONS
The Parkersburg MPO’s surveys were reviewed for variability in travel time and delay at both the corridor and intersection approach levels. In addition to developing the “off-line” link-level time penalties, the corridor level results were also used to develop and test a localized version of Equation 1 (the CV function from Black, Fearon and Gilliam) for further traffic assignment tests. (It is implicit here that intersection approaches are treated as analogous to individual network links, and the study corridors - with an average length of 3.2 miles - are treated as analogous to full O/D travel paths.)

Travel time variability was found to be far lower for full corridors than for individual intersection approaches. At the approach level, the coefficients of variation are reducible to the equation \( CV = -0.56 \ln(\text{average delay}) + 2.82 \). At the corridor level, \( CV \) was only about 10% of intersection-level values. Therefore, the link-level penalties for the “off-line” assignment test were discounted accordingly. (This option was perhaps the most consistent in spirit with the Dijkstra-based approach, but cruder – as it relies on a previous instead of the currently-running model to estimate these penalty values.) The corridor level results were also used to adjust the coefficient values in the travel time CV equation for application to surface streets (Equation 1 – with constant term=0.106, CI exponent=0.776, d exponent =-0.122, unweighted average \( CV=0.12 \), correlation coefficient=0.42, and SEE=0.04). Freeways, expressways, and ramps were left at their original values from Equation 1.

RESULTS OF TRAFFIC ASSIGNMENTS
Tests of traffic assignments in Wheeling focused on three key options – the reliability ratio (added impedance for path building divided by standard deviation of travel time), naïve v. shortest marginal path building algorithms, and the CV equation coefficients for surface streets. The setting of the naïve v. shortest marginal tests are to see locally both the impact of emphasizing travel time variability near the start of the trip and the local importance of finding shortest travel paths. The CV equation coefficients compare the value of using measured variability from studies done nearby to the results cited by Gilliam et. al. from the United Kingdom. Reliability ratio (RR) values between 0.5 and 1.0 were tested, consistent with research reported earlier (3,4). The metrics used to compare results were modeled volume and travel time errors (relative to the local MPO surveys), vehicle-miles of travel (VMT) by type of roadway, and root mean square (RMS) differences in directional volumes and travel times at the link level (relative to a “base case” model where no reliability procedures of any kind were used). Results are summarized in Tables 1 through 4.

VMT overall went down only slightly when invoking the reliability procedures (generally less than 1%) and in some instances shifted slightly to freeways relative to surface streets (Table 1). While effective impedance to travel in the model is increased overall, constraints on zonal trip attractions in the local area model (20 iterations are used for trip distribution for each trip purpose to satisfy attraction-end constraints) dampens the impact. Other model setups could
have caused a more dramatic impact on VMT if no deliberate changes were made in the trip distribution process.

### TABLE 1 Overall VMT and Freeway/Expressway VMT as a Percentage of the “Do-Nothing” Alternative

<table>
<thead>
<tr>
<th>CV Equation Coefficients</th>
<th>Path Building Algorithm</th>
<th>Reliability Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Overall</td>
</tr>
<tr>
<td>UK study only</td>
<td>Naïve</td>
<td>99.5%</td>
</tr>
<tr>
<td>UK study only</td>
<td>Short. Marg.</td>
<td>99.6%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Naïve</td>
<td>99.4%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Short. Marg.</td>
<td>99.6%</td>
</tr>
<tr>
<td>“Off-Line” Penalties Option</td>
<td></td>
<td>98.7%</td>
</tr>
</tbody>
</table>

As shown in Table 2, there are differences in assigned traffic volumes across the various scenarios tested, which are generally not attributable to changes in modeled (average) travel times. The larger impact is in how the estimated variability in travel time is treated. Link level CV estimates largely reflect differences between average and free-flow time and are not uniform, particularly by road type. Having mostly under-saturated flow in this region, as defined in the Highway Capacity Manual (HCM) (18), freeways in this region show little difference between average and free-flow speeds, leading to some volume shifts from surface streets to freeways. The impact of all these items on modeled intersection delays was found to be slight at signalized intersections and also at unsignalized ones with low delays. However, the impact was more noticeable at the higher-delay unsignalized intersections. It should be noted, as described earlier, that “free-flow” speeds (FFS) as estimated for modeling here deliberately include some intersection delay and are therefore not consistent with how FFS is defined in the HCM for some roadway types.

### TABLE 2 RMS (Root Mean Square) Differences in Directional Volumes and Travel Times Compared to the “Do-Nothing” Alternative

<table>
<thead>
<tr>
<th>CV Equation Coefficients</th>
<th>Path Building Algorithm</th>
<th>Reliability Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5 Volume</td>
</tr>
<tr>
<td>UK study only</td>
<td>Naïve</td>
<td>13.1%</td>
</tr>
<tr>
<td>UK study only</td>
<td>Short. Marg.</td>
<td>5.4%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Naïve</td>
<td>11.2%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Short. Marg.</td>
<td>4.1%</td>
</tr>
<tr>
<td>“Off-Line” Penalties Option</td>
<td></td>
<td>13.9%</td>
</tr>
</tbody>
</table>

Finally, the impact on model error compared to traffic counts and travel time surveys were reviewed and shown in Tables 3 and 4. Discrepancies between modeled flows and traffic counts
(Table 3) were found to be minimized by setting the reliability ratio at 0.7. There is a counterintuitive finding that the CV equation coefficients developed from the nearby (WWW) MPO surveys did not work out as well as the “default” values from the UK-based research. The “naïve” path-building algorithm also has slightly better results, indicating that finding shortest travel paths and variability early in these paths is not that important, locally. In all cases, impacts on RMSE were small and could be considered insignificant compared to sampling errors in counts, as depicted in Figure 2 (19, 20). However, the CV coefficients from the Parkersburg region can only be considered provisional until further tests can be conducted with the next model update in that region.

**TABLE 3 Model RMS (Root Mean Square) Error Compared to Directional Daily Traffic Volumes**

<table>
<thead>
<tr>
<th>CV Equation Coefficients</th>
<th>Path Building Algorithm</th>
<th>Reliability Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>UK study only</td>
<td>Naïve</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>37.5%</td>
</tr>
<tr>
<td>UK study only</td>
<td>Short. Marg.</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>38.3%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Naïve</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>39.3%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Short. Marg.</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>38.7%</td>
</tr>
<tr>
<td>“Off-Line” Penalties Option</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>“Do-Nothing” Option</td>
<td></td>
<td>37.9%</td>
</tr>
</tbody>
</table>

Modeled travel times for all tested scenarios compared to the Wheeling MPO surveys are shown in Table 4. Consistent with other travel time tests, there was little difference among the scenarios. As shown in Figure 4, the modeled travel times for urban streets were found to match local field observations far better than other MPO models across the country (who in general still rely on single-equation volume/delay curves to estimate travel times on such facilities), and even exceeded those from other models with specifications similar to the Wheeling model - and well within the sampling errors of the surveys themselves. Finally, computation times were observed to be 8% higher than the do-nothing option using the “naïve” algorithm and 21% higher using the shortest marginal algorithm. (The number of path-building iterations needed to reduce calculated path errors to zero varied somewhat by time interval, but generally required four iterations.)

To address how such procedures would fare under higher levels of congestion than currently exist in Wheeling, separate model runs were made doubling trip generation across the board (by zone and trip purpose), effectively doubling population to 300,000 with no changes in road network or intersection controls. Daily VMT increased 95% with reliability-based procedures and 93% without, full-day average speed declined (9% and 17%, respectively), and the number of congested intersection approaches (LOS D-F) during the typical PM peak hour quadrupled. But the use of these procedures slowed the rate of growth in delay at the most-congested
locations (roughly 20% less growth in delay at the 85th percentile locations compared to no usage of reliability, while for the median locations both sets of procedures had about the same rate of growth in delay).

TABLE 4  Average Travel Time Error (Urban Streets)

<table>
<thead>
<tr>
<th>CV Equation Coefficients</th>
<th>Path Building Algorithm</th>
<th>Reliability Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>UK study only</td>
<td>Naïve</td>
<td>8.6%</td>
</tr>
<tr>
<td>UK study only</td>
<td>Short. Marg.</td>
<td>8.6%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Naïve</td>
<td>8.4%</td>
</tr>
<tr>
<td>WWW &amp; UK</td>
<td>Short. Marg.</td>
<td>8.5%</td>
</tr>
<tr>
<td>“Off-Line” Penalties Option</td>
<td></td>
<td></td>
</tr>
<tr>
<td>“Do-Nothing” Option</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: In all cases, average error for freeways and expressways was 2.6% and for rural 2-lane roads 4.1%, except for the “do-nothing” case (4.2%) and two instances of 4.0% (UK procedure, naïve path-building, and RR= either 0.7 or 0.9).

OBSERVATIONS AND CONCLUSIONS

The expectations at the outset were that locally-based studies of reliability would yield more accurate modeling of travel path selection, locations of congestion/unreliable travel early in the trip would have more impact on travel paths chosen than congestion late in the trip, and that higher reliability ratios would be associated with lower intersection delays. Some but not all of these expectations were realized. A significant impact on vehicle-miles of travel (VMT) was also possible (without changes made to the trip distribution parameters) but did not occur, presumably due to the combined impact of generally light levels of congestion, metropolitan area size, and the use of a “doubly-constrained” gravity model.

These results should be considered tentative given both the low levels of congestion in the region and the typical sampling errors in counts and travel time surveys conducted in the region relative to the differences in the findings. However, model practitioners even in more congested regions may find long-held working assumptions not holding up as they improve upon procedures emphasizing better travel time analysis.

The experience showed that including travel time reliability in regionwide travel forecasts is straightforward. Path building software requires substantial modification, but there is a heuristic that has a good record of finding shortest paths and is consistent with path building algorithms already contained in conventional travel forecasting software packages.

There are ample resources to establish reasonable parameters. Ballpark values for the reliability ratio and the parameters in the coefficient of variation of travel time are available in the literature. These ballpark values can serve until locally-derived parameters can be ascertained.
No compromises need to be made for implementation. Adding travel time reliability does not require modifications to the level of sophistication for any other step of a travel forecasting model.

Computational burden is modest. Computation times were found to increase about 10% by adding the “naïve” algorithm, or 20% with the “shortest marginal” algorithm.

However, it is important that any model have very good delay estimates to begin with before layering on reliability as another consideration for path selection. Additional tests are required on larger and more congested networks.

REFERENCES


