Route Selection Considering Travel Time Variability

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ABSTRACT

Most conventional route guidance systems select the optimal route on the basis of the minimum expected route travel time. However, as a result of the inherent variation in driving conditions, the route travel time that drivers will experience may be longer or shorter than the expected mean travel time. Drivers are likely to have a lower tolerance for experiencing travel times that exceed their expectation, and as a result, drivers may want to select routes that provide them with smaller travel time variation. While this is clearly desirable, it is not clear whether the paths providing the minimum average travel time, are also the optimal paths for other levels of travel time reliability. This paper examines the impact that routing strategy has on route selection. Specifically, the proportion of paths that change when drivers alter their route selection criteria from selecting the minimum travel path computed on the basis of the average travel time to that computed on the basis of say the 95th percentile travel time, is computed. The analysis, conducted using simulation results from a network of a portion of Seattle, Washington, indicates that if a routing system selects routes on the basis of the 95th percentile travel time, then approximately 15% of all routes would be different than the minimum mean travel time routes. The results indicate that there may exist opportunities for improving the reliability of trip travel times by changing the route selection strategy to directly consider travel time variability.

INTRODUCTION

Most conventional route guidance systems select the optimal route on the basis of the minimum expected route travel time. However, as a result of the inherent variation in driving conditions, the route travel time that drivers will experience may be longer or shorter than the expected mean travel time. If the distribution of travel time is symmetrical, then 50% of the time drivers will experience trip times that are longer than the expected average time, and 50% of the time the trip time will be shorter than expected. If the dis-benefit associated with experiencing a travel time that is longer than expected is greater than the benefit of experiencing a travel time that is shorter than expected, then drivers are likely to place a high degree of importance on minimising the variability or uncertainty in their travel times.

For example, consider drivers travelling from an origin to a destination for which two alternate paths exist. Path 1 provides an expected travel time of 30 minutes, with a standard deviation of 10 minutes. Path 2 provides an expected travel time of 40 minutes, with a standard deviation of 2 minutes. If the driver elects to use path 1, then on average, she will experience a travel time of 30 minutes. However, assuming travel times are normally distributed, there is also a 2.5% chance that she will experience a travel time of 50 minutes or longer, or a travel time of 10 minutes or shorter. If a penalty exists for a longer than expected travel time, then the driver is likely to want to reduce the likelihood of experiencing a longer than expected travel time. Since we assume that the driver cannot alter the distribution of travel times associated with a route, the only option remaining to the driver is to select a route that provides the minimum travel time at some specified level of tolerance. Thus, in the current example, if the driver can only tolerate being later than expected 1 out of every 20 trips (i.e. 5%), then she would compare the 95-percentile travel times of the two available routes, rather than the mean travel time. Consequently, she would associate a travel time of 50 minutes with path 1 and 44 minutes with path 2. With this level of tolerance, she would elect to use path 2.

Research in the area of in-vehicle route guidance systems has examined many different route selection criteria including minimum distance, minimum expected travel time, avoidance of certain roadway types (e.g. toll roads), and maximising the use of specific roadway types (e.g. freeways). More recently strategies based on multiple objectives have been examined [1,2].

Little work has been reported in the literature in which variability of travel time has been explicitly considered as a routing objective. Despite this, the importance of travel time variability has been demonstrated. Senna [3] investigated the influence that travel time variability has on the value that travellers place on time. Using stated preference survey data, Senna demonstrated that risk averse travellers, those for whom arriving later than expected at their destination has a higher penalty than the benefit of arriving earlier than expected, are willing to pay premiums to reduce the risk of very long trip times (even when such long trip times are relatively unlikely to occur).

As part of a major study into driver routing behaviour in the Los Angeles area, Abdel-Aty et al [4] have also demonstrated the importance of travel time variability in driver route selection strategies on the basis of stated preference data.

While the issue of driver tolerance to travel time variability is clearly important, it is not clear that typical network conditions give rise to alternate routes in which the route providing the minimum mean travel time, is not also the best route for other levels of travel time variability tolerance. This paper examines the impact that drivers' tolerance for travel time variability has on the route selection process. Specifically, this paper attempts to determine whether routes selected on the basis of minimum mean travel time are likely to also be selected if drivers desire a degree of travel time reliability that is greater than 50% (i.e. variability associated with the mean).

DESCRIPTION OF TEST NETWORK AND DATA

Since link travel time data were not available for field conditions, this study makes use of simulation results from the Seattle Case Study, conducted by Mitretek Systems for the Joint Program Office of the US Department of Transportation [5,6]. In this study, the INTEGRATION traffic simulation model was used in conjunction with a regional planning model to simulate the congested I-5 corridor north of the Seattle, Washington central business district for the 3.5 hour AM peak period of a typical weekday. The network covers an area of approximately 300 square kilometres and is modelled with 2,200 links and 2,357 O-D pairs. During the 3.5 hour AM period, 350,000 vehicles are simulated. An extensive model validation exercise was completed to ensure that the model results adequately reflected existing network conditions. In general the process was demonstrated to produce freeway travel times within 10% of estimates at 30 minute intervals over the peak period and average link flows for the entire network were demonstrated to be within plus/minus 15% [6].

The Seattle study data sets represented the best travel time data available to the authors at the time of this study. From these data, the average and standard deviation of link travel times were compiled for each 15-minute period (14 periods in total) for all links within the network. These link travel time data were used within the subsequent analysis. It must be noted that link travel time data represented the time required to traverse the links and complete any turning manoeuvre at the downstream end of the link. Thus, in determining shortest paths on the basis of these data, there is no differential turn penalty associated with turning movements.

EVALUATION RESULTS

A total of 570 O-D pairs were randomly selected from the 2,357 O-D pairs in the network. A departure time for each O-D pair was also randomly selected from within the 3.5 hour period. The k-shortest path algorithm was used to identify the 20 shortest paths between each selected O-D pair. The results from the k-shortest path algorithm were post processed to address two characteristics of the k-shortest path algorithm. First, the k-shortest path algorithm identifies the routes associated with the k-shortest route travel times, therefore, if two routes provide the same travel time, the k-shortest path algorithm may identify more than k individual routes. Second, the k-shortest path algorithm does not ensure that paths are loopless, so each identified path must be assessed to discard paths that contain loops. Finally, a maximum of the 10 shortest paths between each of the 570 selected O-D pairs were retained for further analysis.

For each path, the mean and standard deviation of the path travel time was determined. This process has been described elsewhere in the literature [7]. The path providing the minimum mean travel time was identified. Figure 1 illustrates the mean and distribution of route travel times associated with the sample of 570 O-D pairs.

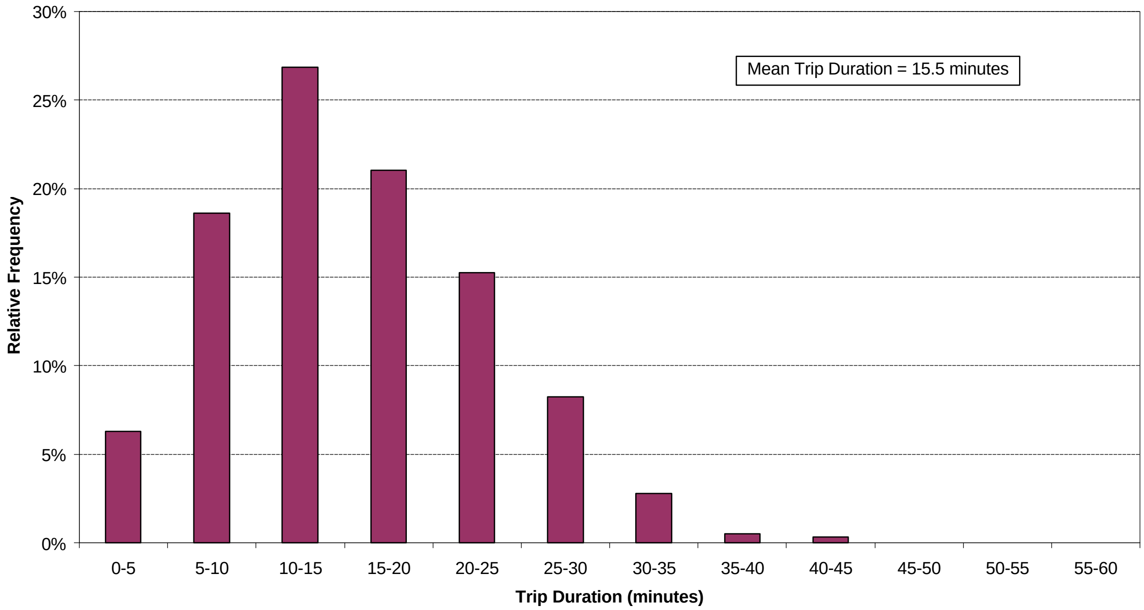

Figure 1: Trip length distribution for sampled O-D pairs based on minimum mean route travel time

Figure 1 illustrates the distribution of route travel times that result when the routing criterion is to minimise expected route travel time. However, if drivers are risk averse and have a different tolerance for the level of travel time variability associated with a route, then it is possible that a routing policy other than one that provides the minimum mean travel time will result in a different route being recommended for use. The question that remains to be answered is what proportion of trips are likely to be affected.

Figure 2 illustrates the proportion of O-D paths that changed as a result of the change in driver tolerance to travel time variability. Three observations can be made on the basis of these results;

- First, as drivers become less tolerant of trip travel times that exceed their expectation (i.e. they require a greater certainty of the expected trip time and become increasing risk averse), a greater proportion of new paths are selected in place of the paths originally selected on the basis of the minimum mean travel time.
- Second, the number of paths that are changed is substantial; 10% of the paths are changed when drivers require a 85% confidence level in their expected travel times, and almost 15% of the paths are changed when drivers require a 95% confidence level.
- Third, the number of paths that change appear to increase exponentially as a function of the drivers' desired level of confidence in their expected route travel times.

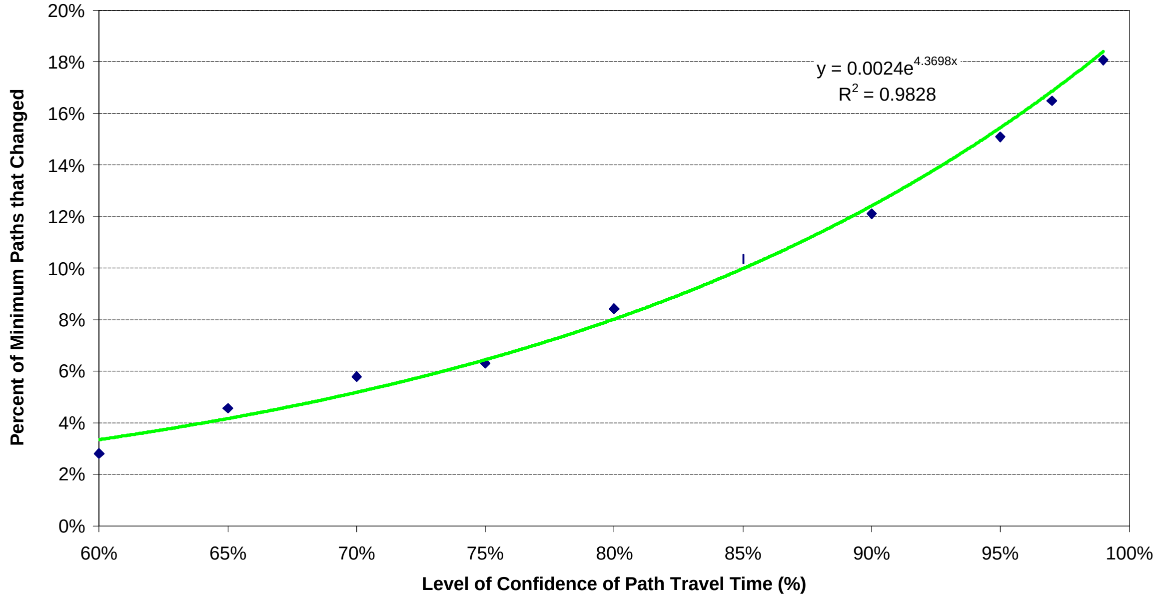

Figure 2: Percent change in path selection as a function of driver tolerance for travel time variability (All trips)

The proportion of routes likely to be altered as a function of the length of the trip was also examined in an effort to determine if route variability is likely to be of greater concern for drivers making short trips or long trips. The proportion of paths that change was determined for three trip length classifications, namely short trips having trip travel times less than 10 minutes, medium trips having travel times between 10 minutes and 20 minutes, and long trips having trip travel times of 20 minutes or more. The results suggest that the percent of minimum paths that change is not substantially different for the different trip lengths.
The study also examined the trade-off that drivers make when they stipulate their level of tolerance. For example, using the example described in the introduction, the benefit to the driver of taking path 2 instead of path 1 is 6 minutes (i.e. 50 - 44 minutes) when evaluated at the 95% level of confidence. However, on average, the cost associated with obtaining this additional travel time reliability is equal to 10 minutes (i.e. 30 - 40 minutes). Another interpretation would be that for highly risk averse travellers, selecting route 2 instead of route 1 would permit the trip departure to be delayed by 6 minutes (assuming that the time-dependent link travel times experienced for both departure times are the same). However, the premium for reducing the risk can be measured as the difference between the mean travel time of route 2 and route 1, in this case 10 minutes. Therefore, on average, the risk average traveller that chooses route 2 would spend an additional 10 minutes travelling per trip than if route 1 were selected, but by doing so, would limit their trip travel time variability.

The benefit and cost of selecting routes on the basis of some level of driver tolerance is computed using Equations 1 and 2.

$$\Delta_C = \frac{1}{n}\sum_i \left(t_n^i - t_o^i\right) \qquad [1]$$

$$\Delta_B = \frac{1}{n}\sum_i \left(t_n^{z,i} - t_o^{z,i}\right) \qquad [2]$$

where:

Δ_C = average cost associated with changing paths (seconds)
Δ_B = average benefit associated with changing paths (seconds)
t^i_n = mean travel time along new route for O-D pair *i* (seconds)
t^i_o = mean travel time along original fastest route for O-D pair *i* (seconds)
$t^{z,i}_n$ = travel time along new route for O-D pair *i* for confidence level *z* (seconds)
$t^{z,i}_o$ = travel time along original fastest route for O-D pair i for confidence limit *z* (seconds)

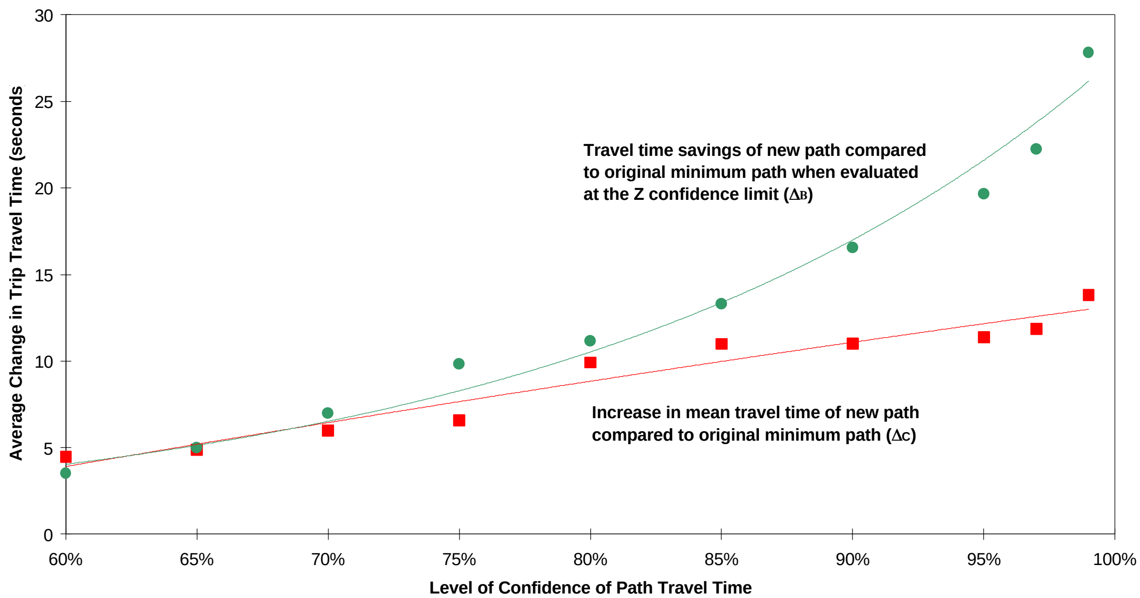

Figure 4: Average change in average trip time and Zth trip time as a function of desired level of confidence.

Figure 3 illustrates the average benefit (Δ_B) and cost (Δ_C) associated with changing routes for a specified level of confidence in the trip travel time. Two observations can be made. First, the average change in route travel time is relatively small for both benefits (Δ_B) and costs (Δ_C) as compared to the average trip duration of 15.5 minutes. Second, the benefits (Δ_B) are greater than the costs for all but the lowest level of confidence.

These results seem to indicate that although a substantial number of alternative routes would be selected under a risk-averse routing policy (as compared to the strategy of minimising mean travel time), the average benefit (and cost) of doing so appears to be very small.

To further interpret the results illustrated in Figure 3, the distribution of benefits associated with individual trips ($t^{z,i}_o$ - $t^{z,i}_n$) is examined for a level of confidence of 99% (Figure 4). These results indicate that for more than 70% of the trips for which routes changed, the benefit and cost associated with routing on the basis of a defined level of confidence in trip times are less than 30 seconds. Consequently, there does not appear to be much practical benefit for travellers making these trips to explicitly consider travel time reliability.

However, the results also show much larger benefits, up to 6 minutes, for a small number of trips. For these trips there may exist practical value in selecting routes on the basis of travel time variability.

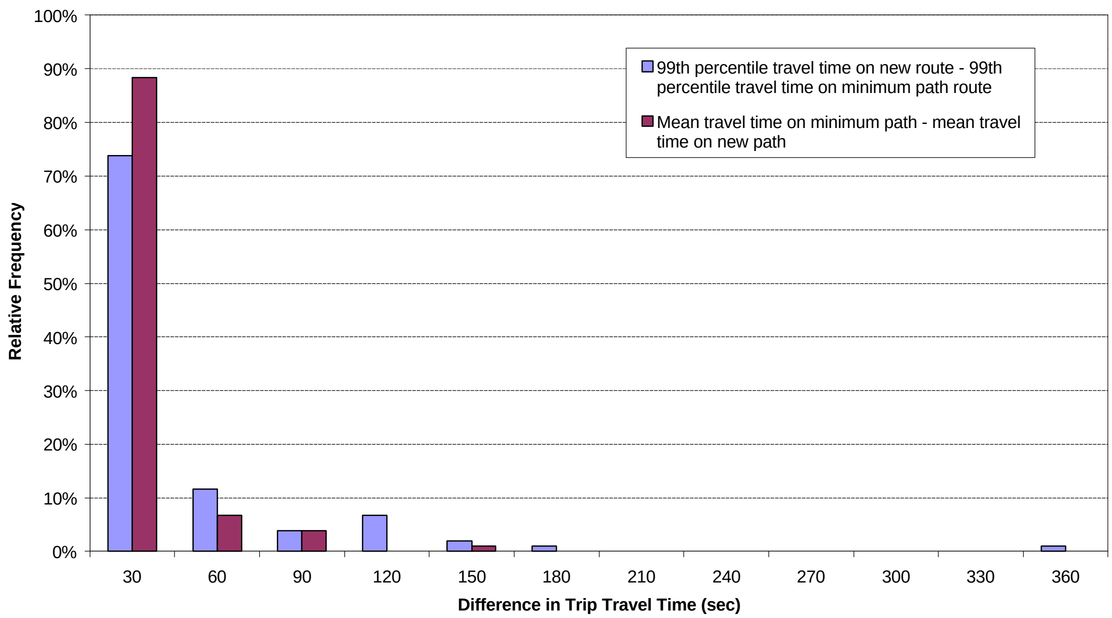

Figure 5: Frequency distribution of changes in individual trip duration for routes that are switched at the 99% level of confidence

CONCLUSIONS AND RECOMMENDATIONS

This paper has quantified the importance of explicitly considering travel time reliability in the route selection process. For the simulated network data, it was found that up to 15% of routes would differ from the minimum mean travel time path when routing on the basis of a higher degree of travel time reliability. For the majority of these paths, the difference in travel time between the selected path and the minimum path computed on the basis of the mean link travel time, was very small relative to the trip duration. However, for a small proportion of trips, there appears to be sufficient difference in the trip time reliability that explicitly considering trip time reliability would be of some practical value

It was noted that the application of the k-shortest path algorithm to the simulated link travel time data did not incorporate differential turning movement penalties. It is hypothesised that the use of turning movement specific link travel time data (mean and variance) would increase the difference between the mean and variance of path travel times. This may result in a greater number of paths for which the benefit of explicitly considering the travel time variability would be of practical value.

ACKNOWLEDGEMENT

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