Considering Risk Taking Behavior in Travel Time Reliability

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Anthony Chen
Will Recker

\(^1\) Department of Civil and Environmental Engineering
Utah State University; Logan, Utah 84322-4110, U.S.A.
achen@cc.usu.edu

\(^2\) Department of Civil and Environmental Engineering and
Institute of Transportation Studies
University of California, Irvine
wwrecker@uci.edu

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Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.lts.uci.edu
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Anthony Chen
Assistant Professor
Department of Civil and Environmental Engineering
Utah State University
Logan, UT 84322-4110, USA
Email: achen@cc.usu.edu

Will Recker
Professor of Department of Civil Engineering and
Director of Institute of Transportation Studies
University of California
Irvine, CA 92697-3600, USA
Email: wwrecker@uci.edu

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ABSTRACT
A better understanding of route choice and the factors that influence the path chosen could significantly improve the opportunities to make the network performance better. The links between network performance, demand and supply variations, and the resultant traveler behavior are poorly understood. Travelers with different behaviors may respond differently to network uncertainty caused by demand and supply variations. In this paper, we examine the effect of considering risk taking behavior in route choice model and its impact on the estimation of travel time reliability of a road network subject to demand and supply variations. Numerical experiments are also conducted to investigate how the different route choice models affect network performance.

Keywords: route choice, risk taking behavior, travel time reliability
1. INTRODUCTION

How well a road network performs can be measured in terms of traffic volumes and travel times. During peak-hour traffic, congestion develops in urban areas because of excess demand over the available supply. This traffic pattern generally repeats itself on a daily basis, which is often referred as recurrent congestion. Another type of congestion, known as non-recurrent congestion, is caused by planned/unplanned events that disrupt the normal operations of a road network, causing a reduction of the roadway capacity and an increase in travel time. Such events include lane blockage due to construction, traffic accidents, bad weather, landslides, earthquakes, etc. In addition to these traffic disturbances that cause variations in network capacity, travel demands are subject to change depending on geographic location, time of day, and occurrence of special events. These uncertainties have a strong impact in how users make their route choice decisions. Unfortunately, these uncertainties have rarely been investigated in the route choice (or traffic assignment) models.

The widely accepted route choice model (i.e., deterministic user equilibrium model) originally proposed by Beckman et al. (1956) is based on strong assumptions that the network travel times are deterministic for a given flow pattern and that all travelers are perfectly aware of the travel times on the network and always capable of identifying the shortest travel time route. To overcome the deficiencies of the deterministic model, some researchers have proposed different stochastic user equilibrium models to relax the assumption of perfect knowledge of network travel times, allowing travelers to select routes based on their perceived travel times (Fisk, 1980; Sheffi and Powell, 1982). Due to variations in travelers’ perceptions of travel times, travelers do not always end up picking the correct shortest travel time route. Most of the stochastic route choice models proposed over the last two decades were based on the concept of random utility theory. However, the assumption of network uncertainty remains unresolved.

In general, route choice decision involves tradeoffs between expected travel time and travel time uncertainty. This observation is supported by a recent empirical study by Abdel-Aty et al. (1996) that found travel time uncertainty was one of the important factors in route choice. Specifically, about 54% of the respondents in the survey indicate that travel time uncertainty is either the most important or second most important reason for choosing their daily commute routes. Given the significance of travel time uncertainty in route choice, this paper aims at examining a number of realistic route choice models to capture how travelers make tradeoff decisions between a route that is longer but has reliable travel time versus another route that is shorter but has unreliable travel time according to their risk taking behaviors. In particular, we examine four route choice models classified by the perception error and network uncertainty factors under the consideration of congestion effect. Emphasis will be given to the risk taking route choice models that account for both travelers’ imperfect knowledge of network travel times as well as the variability of these travel times. Then these route choice models will be integrated into a simulation procedure, which accounts for both demand and supply variations, to estimate travel time reliability measures. Since the route choice model is
the core in the estimation of any reliability measures, the incorporation of different route choice models in the simulation procedure will allow us to ascertain whether the difference in route choice models has any impact on the estimation of travel time reliability measures.

1.1 Measures of Reliability of a Road Network

Despite the importance of assessing the reliability of a transportation system, there exist only a few reliability studies limited to two aspects: connectivity and travel time reliability (Bell and Iida, 1997). Recently, Chen et al., (1999, 2000a) introduce "capacity reliability" as a new performance index. This measure addresses the issue of planning for adequate capacity in a road network to accommodate the growing passenger traffic demand. A general theoretical framework for analyzing a degradable transportation system is provided by Du and Nicholson (1997). Here we summarize three reliability measures.

- **Connectivity Reliability:** Connectivity reliability is concerned with the probability that network nodes are connected. A special case of connectivity reliability is terminal reliability, which determines the existence of a path between a specific origin-destination (OD) pair (Iida and Wakabayashi, 1989). For each node pair, the network is considered successful if at least one path is operational. A path consists of a set of roadways or arcs, which are characterized by zero-one variables denoting the state of each arc (operating or failed). Capacity constraints on the arcs are not accounted for when determining connectivity reliability. This type of connectivity reliability analysis may be suitable for abnormal situations such as earthquakes but there is an inherent deficiency in the sense that it only allows for two operating states: operating at full capacity or complete failure with zero capacity. The binary state approach limits the application to everyday situations where arcs are operating in-between these two extremes. Therefore, the reliability and risk assessment results obtained through this approach may be misleading for normal conditions.

- **Travel Time Reliability:** Travel time reliability is concerned with the probability that a trip between a given OD pair can be made successfully within a given time interval and a specified level-of-service (Asukara and Kasahatici, 1991; Bell et al., 1999). This measure is useful when evaluating network performance under normal daily flow variations. Bell et al. (1999) proposed a sensitivity analysis based procedure to estimate the variance of travel time arising from daily demand fluctuations. Asakura (1996) further extended the travel time reliability to consider capacity degradation due to deteriorated roads. He defined travel time reliability as a function of the ratio of travel times under the degraded and non-degraded states. This type of reliability can be used as a criterion to define the level of service that should be maintained despite the deterioration of certain arcs in the network. When the ratio is close to unity, it is essentially operating at ideal capacity, whereas when it approaches infinity, the destination is not reachable.
because certain arcs are severely degraded. This extreme case is consistent with
the definition of connectivity reliability.

- **Capacity Reliability**: Capacity reliability is concerned with the probability that
the network can accommodate a certain volume of traffic demand at a required
service level (Chen et al., 1999, 2000a). Arc capacities for a road network can
change from time to time due to various reasons such as the blockage of one or
more lanes due to traffic accidents, and are considered as random variables. The
joint distribution of random arc capacities can be experimentally obtained or
theoretically specified. Capacity reliability explicitly considers the uncertainties
associated with arc capacities by treating roadway capacities as continuous
quantities subject to routine degradation due to physical and operational factors.
Readers may note that when the roadway capacities are assumed to take only
discrete binary values (zero for total failure and one for operating at ideal
capacity), then capacity reliability includes connectivity reliability as a special
case. Also, since arc travel times are a function of arc flows and capacities, any
measure of network capacity reliability must also involve some measure of
network travel time reliability. Recently, Yang et al., (2000) further extended the
capacity reliability to include travel time reliability constraints while determining
the maximum reserve capacity of the road network.

The above reliability measures are useful for assessing different impacts related to the
performance of the road network. However, an important issue still remains as to what
type of route choice model should be used to model traveler behavior in estimating the
reliability measures. Except one study by Chen et al. (2000b), all studies above have
used either the simple deterministic or stochastic user equilibrium route choice models
without network uncertainty. In Chen et al. (2000b), the effect of different route choice
models on the estimation of network capacity reliability was examined. They found that
travelers who exhibit different risk sensitive behaviors would most likely to favor some
arcs more than others based on their risk taking preferences. This results in lower values
of network capacity reliability for certain demand ranges. In a similar spirit, this paper
also investigates the effect of different route choice models on the estimation of travel
time reliability. However, we focus on the different risk taking route choice models that
account for both perception error and network uncertainty when estimating the travel
time reliability measures.

This paper is organized as follows. The next section provides a review of four route
choice models under the presence congestion using two factors: perception error and
network uncertainty. This is followed by a discussion of the implementation of these
route choice models. The simulation procedure, which integrates these route choice
models into the estimation of travel time reliability, is presented. A case study is used to
illustrate the application of the proposed simulation procedure. Finally, we present some
concluding remarks based on the results conducted in the numerical experiment.
2. ROUTE CHOICE MODELS

In the route choice literature, several models have been proposed which differ in (1) the characterization of the arc travel times, (2) the traveler’s knowledge of the travel times on the network, and (3) the route choice criteria of each individual traveler. In general, these route choice models under the presence of congestion can be grouped into two factors:

(i) Introduction of perception errors for the traveler to account for imperfect information.
(ii) Inclusion of network uncertainty to account for the stochasticity of network travel times.

A broad classification of route choice models based on the inclusion of both factors is provided in Table 1. In each model, the travel time for every arc on the network is assumed to be an increasing function of the flow of vehicles on the arc. Each traveler is assumed to make route choices to minimize his or her cost, which is a direct function of the travel time on the network. Below briefly summarizes these four classes of route choice models.

2.1 DN-DUE Model

The model most widely used in practice is the deterministic route choice model (i.e., user equilibrium model). Each traveler is assumed to have perfect knowledge of the network travel times on all possible routes between his/her OD pair. Each traveler’s route choice criterion is to minimize the known value of the route travel time, which is obtained by adding up the travel times on all the arcs belonging to the route. The choices of routes by all travelers result in a network flow allocation such that all used routes between every origin and destination have equal travel times and no unused route has a lower travel time according to Wardrop’s First Principle (1952). Network uncertainty is not considered in this model. The DN-DUE model was previously used by Asakura and Kashiwadani (1991) to estimate road network reliability caused by daily fluctuation of traffic flow and by Chen et al. (1999, 2000a) to estimate network capacity reliability subject to degradable arc capacities.

2.2 DN-SUE Model

Due to the unrealistic assumption that all travelers have perfect knowledge of the network conditions, the DN-SUE model relaxes this stringent assumption by introducing a perception error into the route choice decision. In this model, each traveler is assumed to have some perception of the mean travel times on each arc of the network, which include a random error term. Each traveler’s route choice criterion is to minimize the perceived value of the route travel time, which is obtained by adding up the perceived travel times on all the links belonging to the route. The choices of routes by the travelers result in a
network flow allocation such that no traveler can reduce his/her perceived travel time by changing to another route. It should be noted that this model only accounts for the randomness in the travelers’ perceived travel times. Arc travel times are still modeled as a deterministic function of the traffic flow on the arc using the mean values. This model is the bridge between stochastic network problem and discrete choice analysis (Sheffi and Powell, 1982), where the stochastic network is modeled using mean values of arc travel times and discrete choice analysis is used to model users’ perception of these mean travel times. Bell et al. (1999) and Asakura (1999) applied the logit-based DN-SUE model (Fisk, 1980) to evaluate performance reliability of a road network, while Lam and Xu (1999) and Chen et al. (2000b) used the probit-based DN-SUE model (Sheffi and Powell, 1982) for network reliability assessment.

2.3 SN-DUE Model

In the SN-DUE model, network uncertainty is explicitly considered but perception error is ignored. Arc travel times are treated as random variables. For a given set of flows, there is a probability distribution associated with the arc travel times, which describes the variations in the travel times experienced by the travelers on the network. Such variations could result from the differences in the mix of vehicle types on the network for the same flow rates, differences in driver reactions under various weather and driving conditions, differences in delays experienced by different vehicles at intersections, etc.

Because the travel time variability is included in this model, different travelers may respond to such variations differently depending on their risk taking preferences. Depending on the behavioral nature of travelers, they are classified as risk averse, risk prone or risk neutral. The risk in this case is the variance associated with network travel times. For instance, a risk averse traveler will trade off a reduction in travel time variability with some increase in expected travel time, whereas a risk prone traveler may choose a route with a greater variability so as to increase the possibility of a smaller travel time. A risk neutral traveler would choose a route based on only expected travel times without consideration of its variability. It should be noted that the risk neutral model is essentially the DN-DUE model in which each traveler makes his/her route choice based on the mean arc travel times.

Each traveler type is assumed to associate a disutility with each arc that is a function of the arc travel time and the traveler’s risk taking behavior. The route choice criterion in this model is to minimize the disutility associated with a route. The choices of routes by the travelers result in a flow allocation such that no traveler can reduce his/her expected disutility by changing to another route.

In this model, travelers are assumed to have perfect knowledge of the variable nature of network travel times. This model may be suitable for peak-hour traffic where regular commuters have a good idea of the mean and variance of network travel times. Previously, Chen et al. (2000b) applied the SN-DUE model to estimate network capacity reliability subject to degradable arc capacities.
2.4 SN-SUE Model

A truly stochastic model should consider both the traveler perception errors as well as the stochasticity of network travel times. A stochastic route choice model that accounts both for variable network travel times as well as a method to model different traveler responses to network travel time variability by assuming different risk taking behaviors was presented in (Mirchandani and Soroursh, 1987). This model also accounts for the variations in each individual traveler’s perception errors. The mean and variance of the travelers’ perception errors are sampled from distributions defined over the population. Thus the perceived distribution of travel times on the network by each traveler is a function of the actual distribution of the network travel times as well as the distribution of the traveler’s own perception error.

Similar to the SN-DUE model, travelers are either risk averse, risk prone, or risk neutral based on the assumptions about the behavioral preference of travelers. Then, each traveler type is assumed to associate a disutility with each arc that is dependent on the arc travel time, the individual traveler’s perception error distribution, and his/her risk taking behavior. The route choice criterion in this model is to minimize the perceived disutility associated with a route. The choices of routes by the travelers result in a flow allocation such that no traveler can reduce his/her perceived expected disutility by changing to another route. Chen et al. (2000b) also applied the SN-SUE model to the capacity reliability problem and examined the effect of different route choice models on estimating network capacity reliability.

3. IMPLEMENTATION OF THE ROUTE CHOICE MODELS

The implementation for the two route choice models under the deterministic network, DN-DUE and DN-SUE, is based on the Frank-Wolfe (FW) algorithm and the Method of Successive Averages (MSA) algorithm, respectively. The details are provided in Sheffi (1985). Here we are concern about the implementation of the route choice models under a stochastic network with risk taking behavior. The issues of implementing different risk taking route choice models are (a) the estimation of arc travel times and variances, (b) the estimation of travel disutility functions, (c) the assumptions with regard to the perception error distributions, and (d) the choice of stochastic loading and solution algorithm. We discuss these and related issues below.

(a) Arc travel times and variances are assumed to be directly dependent on the flow on the arc. The travel time is estimated by the standard BPR (Bureau of Public Road) arc travel time function. Depending on the availability of data to estimate travel time variability, these arcs are assumed either to have deterministic travel times that vary only with their flows or to follow certain distribution that characterizes the variation associated with the time moving along the arc.
(b) In order to model travelers with different risk taking behaviors, disutility functions representing specific behavioral types are needed. Following the study by Tatineni et al. (1997), we also use the exponential function, which is one of the most widely used disutility functions reported in the decision-making literature to study the different risk taking behaviors. An advantage of using the exponential function is that the disutility associated with a route can be estimated by summing the arc disutilities on a given route (i.e., additive assumption holds). This allows the classical Dijkstra-type shortest path algorithm to be used in finding the minimum expected disutility route. Assume that a route with a travel time of 0 minutes has a disutility of 0 and a route with a travel time of 5 minutes has a disutility of 1, the disutility functions estimated for the different risk-taking behaviors are as follows:

\[
\text{Risk Averse: } DU(t) = 0.309 \left( \exp(0.289 \ t) - 1 \right)
\]

\[
\text{Risk Prone: } DU(t) = 1.309 \left( 1 - \exp(-0.289 \ t) \right)
\]

Here \( t \) is the travel time in minutes for a given route. For risk neutral behavior, we simply use the DN-SUE model, which uses a linear disutility function, by setting the disutility equal to the expected travel time. The shapes of these different risk taking behaviors are provided in Figure 1. The details of the derivation of the parameters for the disutility function can be found in Tatineni (1996).

(c) For the risk taking route choice models, each traveler is assumed to have some knowledge of the stochasticity of the network travel times in the form of a distribution, which includes a variable perception error (Mirchandani and Soroursh, 1987). The traveler’s perception error distribution (i.e., mean and variance) is then sampled from pre-specified distributions over the population. The perception error of individual travelers is assumed to follow a normal distribution similar to the probit-based DN-SUE model. In addition, the risk taking route choice models account for the variations in each individual traveler’s perception error. That is, each individual traveler experiences a different travel time for a given set of flows. This is different from the DN-SUE model that only accounts for the randomness of the travelers’ perceived travel times and treats the randomness of arc travel times in the form of expected values.

(d) In the SN-SUE model, travelers choose routes to minimize the perceived disutility according to their risk taking behavior. Since there exists no closed-form solution for the route choice probability, a Monte Carlo sampling technique is performed to construct a stochastic loading. At each iteration of the solution algorithm, the origin-destination (OD) flows have to be loaded on the shortest-perceived disutility routes between each OD pair. To find the shortest-perceived disutility routes, at every iteration, several sets of perception errors are sampled and the routes with the shortest-perceived disutilities are found for each sample. Instead of a single all-or-nothing loading, the OD flows are then averaged among every
route found between the origin and the destination. The stochastic flows estimated thus are averaged between successive iterations of the solution algorithm based on a pre-specified averaging rule until terminating criterion is satisfied. This Method of Successive Averages (MSA), as it is generally known, is used to solve the risk taking, stochastic route choice models. The SN-DUE model can be implemented in the same manner by removing the perception error term (See Tatnemi (1996) for details).

4. INTEGRATING RISK TAKING BEHAVIOR INTO TRAVEL TIME RELIABILITY

Travel time reliability is concerned with the probability that a trip between a given OD pair can be made successfully within a given time interval and at a specified level-of-service (Asukura and Kashiwadani, 1991; Bell et al., 1999). There are two potential measures - path travel time reliability and OD travel time reliability - that are of interest to the travelers and traffic managers (Bell et al., 1999). Path travel time reliability is defined as the probability that the travel time of a given path is within an acceptable threshold, while OD travel time reliability measures all relevant paths used by travelers to define an aggregate measure for the level-of-service between a given origin-destination pair. Since the actual travel times on each path may be different, the OD travel time reliability is computed as a weighted average of the travel times on the different paths, where the weights are the path flows. Travelers are more concerned about the path travel time reliability, because it directly affects their route choice decisions. Traffic managers or planners can use the OD travel time reliability as a proxy to evaluate the performance of the network.

The travel time reliability evaluation procedure presented below is based upon a Monte Carlo simulation with random inputs. In this paper, we treat arc capacities and origin-destination (OD) demands as random variables. Assuming that the random variables $C_a$ and $Q_o$ follow a probability distribution, a random variate generator is used to generate the values of $C_a$ for each arc and $Q_o$ for each OD pair that preserve the provided distribution properties. For each set of arc capacities and OD demands generated, four different route choice models discussed in Section 2 are used to estimate the OD and path travel time reliabilities.

The travel time reliability procedure is described as follows:

Step 0: Set sample number $k := 1$.

Step 1: Generate a vector of OD demands $Q_o = \{Q_1, \ldots, Q_o\}$ and/or a vector of arc capacities $C_a = \{C_1, \ldots, C_a\}$.

Step 2: Perform the DN-DUE, DN-SUE, SN-DUE, and SN-SUE route choice models with same the OD demand vector $Q_o$ and arc capacity vector $C_a$.

Step 3: Collect statistics from Step 2 to compute travel time reliability.
Step 4: If sample number \( k \) is less than the required sample size \( k_{\text{max}} \), then increment sample number \( k := k + 1 \) and go to Step 1. Otherwise, terminate the procedure.

5. NUMERICAL EXPERIMENT

In this section, we present some numerical results from our experiments using the different route choice models discussed in this paper to compute OD and path travel time reliabilities for a small test network. Figure 2 shows the test network, which consists of 5 nodes, 7 arcs, and 2 OD pairs. The base demand for OD pairs (1,4) and (1,5) are 15.0 and 18.8, respectively. The free flow travel times for each arc on the network as well as the capacity values are shown in Table 2. Arc travel times are computed by using the standard Bureau of Public Road (BPR) function shown below:

\[
t_a = t'_a \left( 1 + 0.15 \left( \frac{v_a}{c_a} \right)^4 \right)
\]

Here \( v_a, t'_a, \) and \( c_a \) are the flow, free-flow travel time, and capacity on arc \( a \), respectively.

To simplify the computation without losing generality of the analysis, the numerical experiment only focuses on the variations of OD demands and assumes arc capacities to be fixed. We vary the OD demands around the means to reflect the degree of accuracy of the traffic forecasts, which are often uncertain and would vary anywhere from 20 to 60 percent (Mette and Bent, 1996). That is, the standard deviation \( (\sigma) \) of the OD demand is varied in three levels: (1) \( \sigma = 15 \times \frac{q_{\text{max}}}{3} \) for low accuracy demand estimates, (2) \( \sigma = 1.0 \times \frac{q_{\text{max}}}{3} \) for medium accuracy demand estimates, and (3) \( \sigma = 0.5 \times \frac{q_{\text{max}}}{3} \) for high accuracy demand estimates. These three accuracy levels of traffic forecasts can also be interpreted as high-risk scenario, moderate-risk scenario, and low-risk scenario, respectively. Given that both the mean and standard deviation of OD demands are defined, random samples for each OD pair can be generated according to a standard normal distribution as follows:

\[
Q_a = q_a \pm Z \sigma
\]

where:

\[
\begin{align*}
Q_a & = \text{random demand between OD pair (r,s),} \\
Z & = \text{random variable generated from N(0,1).}
\end{align*}
\]

Whenever a negative value for the OD demand is generated, we reset it to have a 1 unit of demand. To ensure high accuracy, we use 10,000 samples in our simulation.
experiment to generate the numerical results for this study. As shown in Table 3, the theoretically computed values of the mean and standard deviation for the OD demands match quite closely with the values estimated from the simulation. Therefore, the number of samples drawn is sufficient to generate a representative distribution of the OD demands.

In order to model the risk sensitive traveler’s route choice behavior, all the arcs in the network are assumed to have some variability associated with their travel times. For arc 1 the variance on the travel time is assumed to be 100 percent of the arc’s free flow travel time. For all other arcs the travel times are assumed to vary up to 10 percent of the arc’s free flow travel time.

5.1 Arc Flow Comparisons for Different Route Choice Models

The complete arc flow patterns comparing different route choice models with different OD demand variances are provided in Figure 3. For the SN-DUE and SN-SUE models, travelers are assumed to be risk averse. In all cases, the average arc flows do not seem to be affected by the different accuracy levels of the traffic forecasts, but have an apparent difference in how each route choice model allocates the flow to the network. On arc 1, which has a higher variability in travel time, both SN-DUE and SN-SUE models that account for network uncertainty allocate less flow whereas both DN-DUE and DN-SUE models that ignore network uncertainty allocate a larger proportion of its flow to this arc. On arc 2, which represents an alternative to arc 1, we notice the opposite effect in that the models assuming risk averse behavior allocate more flow while the models assuming risk neutral (DN-DUE and DN-SUE) behavior allocate less flow. Between the SN-DUE and SN-SUE models (i.e., without and with perception error), we see that the risk averse model without perception error allocate a slightly higher flow to arc 2 compared to the risk averse model with perception error. This demonstrates that the traveler’s perception error can have an effect on flow allocations.

5.2 Path Flow Comparisons for Different Route Choice Models

The complete path flow patterns comparing different route choice models with different OD demand variances are provided in Table 4. There are 6 paths in total serving the 2 OD pairs. Paths 1, 2, and 3 are for OD pair (1,4), and paths 4, 5, and 6 are for OD pair (1,5). Similar to the arc flow comparisons, the mean path flows are fairly similar for all three different OD demand variances, but the variance of path flows increases as the OD demand variance is increased. Also, based on the assumptions of the route choice model, it is apparent that each route choice model allocates a different amount of flow to each path. For example, the DN-DUE model seems to allocate more flow to path 1 and path 4, which both contain the high variability arc, while the two risk averse models (SN-DUE and SN-SUE) allocate more flow to path 2 and path 5 to avoid the high variability arc. It is interesting to see that the SN-DUE model, which assumes to have perfect knowledge about the variable nature of the network travel times, practically assign no flow to path 3.
and path 6 that contain the high variability, while some amount of flow are allocated to
these two paths by the DN-DUE, DN-SUE, and SN-SUE models. The differences in
flow allocation to the paths in the network between the route choice models implemented
without and with perception error are also evident from the results presented in Table 4.
Thus, it would appear that the different assumptions in modeling route choice behavior
could have an effect on the path flow patterns as well as the link flow patterns.

5.3 OD Travel Time Comparisons for the Different Route Choice Models

In Table 5, we show the differences in the average travel times for the two OD pairs for
each route choice model with different OD demand variances. For the DN-DUE model,
the travel times on all used paths are equal so the average travel times are simply
averaged over the number of samples. For the other three models (DN-SUE, SN-DUE,
and SN-SUE), the actual travel times on each path may be different since at equilibrium
only the perceived travel times or disutilities are equal for all used paths. So for these
models, the average travel time between each OD pair is computed as a weighted average
of the travel times on the different paths, where the weights are the path flows.

In general, we notice that for all the models the travel times increase as the OD demand
variances are increased. Since the DN-DUE model is based on the assumption that
travelers choose routes to minimize travel times and base their decisions on perfect
information, the travel time values for the DN-DUE model are, as expected, the lowest
for route choice models. The SN-DUE model that assumes risk averse behavior without
perception error results in the highest travel times among the four route choice models.
This result can be explained as follows: When leaving origin 1, the routes have to include
either arc 1 or arc 2. Arc 1 has a lower free-flow travel time but higher variability in
time travel, while arc 2 has a higher free-flow travel time but lower variability in travel
time. One would expect that the risk averse travelers without perception error would be
more likely to choose arc 2 resulting in higher path travel times, risk neutral travelers
(DN-SUE) would be more likely to choose arc 1, and some risk averse travelers in the
SN-SUE model would choose arc 1 due to perception error and therefore would have
lower OD travel times.

5.4 Effect of Route Choice Models on the Estimation of OD Travel Time
Reliability

In Figure 4, we show the OD travel time reliability curves for both OD pairs (1,4) and
(1,5) for each route choice model for three levels of OD demand variances. On the X-
axis, we plot the threshold value, which can be used as an indicator for level-of-service (a
smaller value indicates a higher level-of-service). The Y-axis is the OD travel time
reliability, which is defined as the probability that the weighted travel time of a given OD
pair is within an acceptable level-of-service. This measure, as mentioned above, is an
aggregate measure of all the relevant used paths serving an OD pair.
As might expected, for lower OD demand variances \( (b=0.5) \), the OD travel time reliability curves have smaller variations among the different route choice models. However, as the OD demand variance increases, the variations of the reliability curves also increase. This apparently decreases the probability that a trip can be made within a specified threshold value on the X-axis (say, 10.1). The OD travel time reliability for OD pair \((1,4)\) is almost 1.0 for all route choice models at \( b=0.5 \), drops to about 0.9 and 0.8 (average of all route choice models) when OD demand variance increases to \( b=1.0 \) and \( b=1.5 \), respectively. Similar results also occur for OD pair \((1,5)\).

An interesting observation is that in all cases the OD travel time reliabilities under the DN-DUE model are always higher compared to the other three models. Since travelers in the DN-DUE model assume to have perfect information and use travel time as the sole criterion for route choice, it is reasonable to have such results. However, for the DN-SUE model, travelers are assumed to make route choices with imperfect information, hence the OD travel time reliability may be slightly sub-optimal resulting in slightly lower OD travel time reliability. For the SN-DUE and SN-SUE models which assume risk averse travelers, route choices are based on minimizing disutilities and perceived disutilities, respectively, which are based on arc travel time variabilities leading to higher OD travel times (see Table 5 also) or lower OD travel time reliabilities. Thus it would seem reasonable that the OD travel time reliability is lower when route choices are assumed to be based on imperfect information and even more so when they are based on minimizing disutilities that are a function of factors other than arc travel times.

5.5 Effect of Route Choice Models on the Estimation of Path Travel Time Reliability

In Figure 5, we show the path travel time reliability curves for all paths connecting the two OD pairs for the medium accuracy of traffic forecasts \( (b=1) \) for each route choice model. Similar to the OD travel time reliability, the X-axis is the threshold value or level-of-service, and the Y-axis is the path travel time reliability which is defined as the probability that the travel time of a given path is within an acceptable threshold. The legend shows the arc sequence of each path. The first 3 paths are for OD pair \((1,4)\) and the second 3 paths are for OD pair \((1,5)\).

For the DN-DUE and DN-SUE models, the path travel time reliability curves are more clustered together compared to the SN-DUE and SN-SUE models that assume risk averse travelers. The same explanation used above also applies here. For both DN-DUE and SN-SUE models, travelers are assumed to make their route choices solely based on travel time. No consideration is given to travel time uncertainty. However, for the SN-DUE and SN-SUE models that consider both travel time and travel time variance, less travelers would choose path 1 \((1->4)\) and path 4 \((1->5)\) because both contain arc 1 which assumes to have a high variability in travel time, while more travelers would choose path 2 \((2->6)\) and path 5 \((2->7)\) that have less variability in travel time. Because more travelers use path 2 and path 5, travel times on these two paths are higher than those on path 1 and path 4. This evidently decreases the travel time reliability for path 2 and path 5. We also
notice that path 3 (1->3->6) and path 6 (1->3->7) are not used in the SN-DUE model since both paths have high variable travel times as well as high travel times. As for the SN-SUE model, both paths 3 and 6 are used due to perception error. Similar results also occur for other OD demand variances (b=0.5 and b=1.5).

5.6 Effect of Risk Neutral, Risk Averse, and Risk Prone Behaviors on the Estimation of Path Travel Time Reliability

Figure 6 examines the effect of risk taking behaviors on the estimation of path travel time reliability. For brevity, we show only path 1 (1->4) and path 2 (2->6), which are two alternatives for OD pair (1,4), for risk neutral (sue-rn), risk averse (sue-ra), and risk prone (sue-rp) behaviors under three OD demand variances. Note that the risk neutral case is the same as the DN-SUE model.

It is apparent that as the OD demand variance is increased, path travel time reliability decreases irrespective of the risk taking route choice models. In all three cases, the risk neutral model consistently shows lower (higher) travel time reliability on path 1 (path 2) compared to the risk averse and risk prone models. This is because the risk sensitive models are concerned about travel time variability on path 1. However, the differences in path travel time reliabilities for the risk averse and risk prone models are minor. We suspect that the traveler’s perception error may have overshadowed the risk taking behavior.

Removing the perception error in each of the risk taking models, we show the complete arc flow comparison for all arcs for risk neutral (due-rn), risk averse (due-ra), and risk prone (due-rp) behaviors under three OD demand variances in Figure 7. Note that under the assumption that travelers do not have any perception errors, the risk neutral model (due-rn) is the same as the DN-DUE model, while due-ra and due-rp models are special cases of the SN-DUE model using different risk taking utility functions (see Section 3). Without the perception error, there appears to have some flow differences for arc 1 and arc 2 for the risk averse and risk prone travelers. Risk prone travelers favor arc 1 more than the risk averse travelers. However, the differences in flow allocations are minor compared to those allocate by the risk neutral model. Thus, it would appear that travel time (in addition to travel time variability) also plays an important role in the route choice process for the risk sensitive travelers.

6. CONCLUDING REMARKS

We have presented four different route choice models under congestion by considering two factors: perception error and network uncertainty. The DN-DUE and DN-SUE models that assume travel time as the sole criterion for minimization are well researched compared to the SN-DUE and SN-SUE models that account for both travel time and travel time variability in their minimization. If travel time variability is interpreted as a
risk in choosing a path, then each traveler's behavioral reaction may be modeled by assuming different risk taking behaviors. The results from these route choice models may have a significant difference depending on the assumptions made for each model. Since the route choice model is the core in the estimation of any reliability measures, it is important to examine how the different assumptions made in the route choice models affect the calculation of reliability measures.

Using these route choice models, we integrated them into a simulation procedure, which accounts for both demand and supply variations, to estimate travel time reliability measures. As a case study, we performed numerical experiments using a simple network with only demand variations. Based on the case study, we found the following conclusions concerning the use of different route choice models in estimating travel time reliability measures.

1. Travelers who exhibit different risk taking behaviors will most likely favor some paths (or arcs) more than others based on the disutility associated with each path (or arc).
2. Perception error may overshadow the risk taking behavior and cause some paths to be used.
3. The weighted OD travel time is lowest for the DN-DUE model and highest for the SN-DUE model.
4. Both OD travel time reliability and path travel time reliability decrease as OD demand variance is increased.
5. OD travel time reliability is lower when route choices are assumed to be based on imperfect information and even more so when they are based on minimizing disutilities that are a function of factors other than arc travel times.
6. Depending on the variability of path travel time, path travel time reliability may be lower or higher based on the risk taking preference.

It should be noted that the results and conclusions are only relevant to the particular network and parameters used in this study. Further work is necessary to verify the results of this study.
7. REFERENCES


Figure 1. Disutility Functions for the Risk-Taking Route Choice Models

Figure 2. Test network
Figure 3. Arc Flow Comparisons for the Different Route Choice Models with Different OD Demand Variances
Figure 4. Effect of Route Choice Models on the Estimation of OD Travel Time Reliability
Figure 5. Effect of Route Choice Models on the Estimation of Path Travel Time Reliability for OD Demand Variance (b=1.0)
Figure 6. Effect of Risk Neutral, Risk Averse, and Risk Prone Behaviors on the Estimation of Path Travel Time Reliability
Figure 7. Arc Flow Comparisons for the Risk Neutral, Risk Averse, and Risk Prone Behaviors with Different OD Demand Variances
Table 1. Classification of Route Choice Models

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where DN = Deterministic Network
SN = Stochastic Network
DUE = Deterministic User Equilibrium
SUE = Stochastic User Equilibrium

Table 2. Arc Free-flow Travel Times and Arc Capacities

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Table 3. Statistical Properties of OD Demands

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### TABLE 4. Path Flow Comparisons for Different Route Choice Models with Different OD Demand Variances

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