Analysis of Reliability of Transportation Networks

BY

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AUTHORIZATION PAGE

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ABSTRACT

An efficient and reliable transportation system is essential to the economy of a nation or region because it provides accessibility and promotes the safe and efficient movement of people and goods. Also, a reliable network plays an important role for the maintenance and repair of other lifeline systems. Thus, it is necessary and important to study the reliability of a road traffic network.

Travel time reliability and capacity reliability are considered to be two useful measures of the performance of a road traffic network. The former is concerned with the probability that a trip between a given origin-destination pair can be made successfully within a specified interval of time for a given level of traffic demand in the network; while the latter is given as the probability that the network can accommodate a certain traffic demand at a required level of service. Determination of both reliabilities requires accounting for drivers' route choice behavior. The first part of the thesis analyses the comprehensive integration of both travel time and capacity reliability and discusses the practical use of this study.

The second part of the thesis provides a day-to-day analysis of the reliability of commuting time and trip scheduling under the Advanced Traveler Information System (ATIS). An analysis of travel cost reliability, which is considered as how likely the road users or commuters will be satisfied with their resultant individual travel costs, is carried out in this part to assess the network performance. A simple network with parallel routes and bottleneck congestion is taken into consideration to simulate the departure
Abstract

time and the route choice decisions of commuters to minimize total travel time and scheduling delay cost. There are two major factors influencing the decisions of drivers in their departure time and route choices: their accumulated travel experience and information provided by ATIS. A simple experiment has been carried out for investigating trip scheduling reliability of this network system.
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CHAPTER 1

INTRODUCTION

1.1 General Background

The development of a nation or region depends in large extent upon an efficient and reliable transportation system to provide accessibility and promote the safe and efficient movement of people and goods. Moreover, a reliable transportation system is essential for maintenance and repair of other lifeline systems. Thus the importance of guaranteeing an acceptable level of transportation service cannot be overemphasized. However, in reality smooth traffic flow in a road network is often subject to interruptions by the events such as earthquakes, floods, traffic accidents, adverse weather and slope failure, for periods varying from a few hours to a few years. Thus it is necessary and important to study the reliability of a road traffic network.

1.2 Previous studies of reliability

With increasing needs for better and more reliable services, many systems (e.g., electrical power systems, water distribution system and communication networks) have incorporated reliability analysis as an integral part in their planning, design, and operation (Ang and Tang, 1990). However, reliability analysis has received very limited attention in the context of road traffic networks in spite of its importance. A few existing reliability studies of road networks are mainly limited to three aspects: connectivity, travel time reliability and capacity reliability (Wakabayashi and Iida, 1992; Bell and Iida, 1997, Chen et al., 1999). A general theoretical framework and a review for...
reliability analysis of degradable transportation systems can be found in Du and Nicholson (1997).

1.3 Definitions of different types of reliabilities

1.3.1 Connectivity reliability

Connectivity reliability is concerned with the probability that the network nodes remain connected. A special case of the connectivity reliability is the terminal reliability, which concerns the existence of a path between a specific origin-destination (O-D) 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 components (roadways or links) which are characterized by zero-one variable denoting the state of each link (operating or failed). Capacity constraints on the links are not accounted for when finding the connectivity reliability. This type of reliability analysis might 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. This binary state approach limits the application to everyday situations where links are operating in-between these two extremes. The approach may thus result in misleading results of reliability and risk assessment of a road network.

1.3.2 Travel time reliability

Travel time reliability is introduced to reflect variation of O-D travel time (Asakura and Kashiwadani, 1991). It is concerned with the probability that a trip between a given O-D pair can be made successfully within a specified interval of time. Bell et al. (1998) proposed a sensitivity analysis based procedure to estimate the variance of travel time arising from daily demand fluctuations. Asakura (1996) examined travel time reliability
in the case of capacity degradation due to deteriorated roads. Travel time reliability is given as a function of the ratio of travel times under the degraded and non-degraded states. 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 links are so severely degraded. This extreme case is consistent with network connectivity reliability. Generally, the measure of travel time reliability is useful to evaluate network performance in terms of service quality that should be maintained in daily operations.

1.3.3 Capacity reliability

General speaking, the aforementioned connectivity and travel time reliability measures are useful for assessing the quality of service that is of interest to individual drivers. The capacity reliability of the network – the probability that the network capacity can successfully accommodate a certain level of O-D demand at an acceptable service quality – should be considered an important and meaningful measure of overall system performance that is of interest to system managers. The reason is simple: the connectivity between the origin and the destination is a necessary condition for the successful operation of a road network, but it is not a sufficient condition. The success of the O-D connection should also ensure the availability of the required O-D capacity. Thus capacity reliability should be considered together with travel time reliability. Efforts to incorporate capacity into reliability have been made for communication networks (Aggarwal, 1985; Chan el al., 1998), water distribution system (Li et al., 1993), electric power system (Billington and Li, 1994) to determine the maximum flow of the networks. However, the approach is not directly applicable to a road traffic network where the capacity modeling characteristics is quite different in the followings.
• The movement of flows in the road network involves people rather than pure physical commodities treated in classic network flow theory, and the travel delay will increase with increasing flow as a result of congestion. Thus drivers' route choice behaviors have to be considered in determining maximum flow of a congested road network.

• Conventionally, the capacity of a physical commodity network is defined as the largest possible sum of flow from a source to a sink capable of being accommodated, while honoring a given capacity on each link. Nevertheless, road network capacity or maximum flow level should be specified with regard to its level of service such as O-D travel time.

• In addition, multiple O-D pairs exist and the flows between different O-D pairs are not exchangeable or substitutable in modeling road network capacity. It is thus important how to define the O-D demand pattern that greatly influences the resultant value of road network capacity. It is important how to select the target O-D matrix appropriately for capacity calculation.

The above characteristics make the modeling of road network travel time and capacity a quite complex, yet intriguing problem. Recently, Chen et al. (1999) conducted extensive simulation study of network capacity reliability and sensitivity analysis using the concept of reserve capacity of a road network proposed by Wong and Yang (1997).
1.3.4 Travel cost reliability

Apart from the aforementioned travel time reliability, we can also consider, by adopting a similar concept, the travel cost reliability. Travel cost reliability is another definition of network reliability which is that a network is regarded as reliable if the expected trip costs are acceptable even when users are extremely pessimistic about the state of the network (Bell, 1999). It can be measured by the infrastructure of a network system and the behavioral responses of the road users. The network infrastructure can be accessed by connectivity reliability, travel time reliability and capacity reliability. However, the factor of commuters’ behavioral responses is difficult to assess from these three indicators only. One of main concerns of travel cost reliability is the utility function of each commuter and it reflects the characteristic of the commuter about the monetary value of time of schedule delay (i.e. early or late arrival) of his trip. Note that the utility function is not useful in assessing the travel time reliability.

1.4 Advanced Traveler Information System (ATIS)

An interesting policy option to reduce travel time and schedule delay cost is to provide travelers with information about both congested conditions and travel time variances. This will allow commuters to more accurately minimize their expected costs of travel and would presumably increase net social benefits. Having been provided with the real time traffic information, each road user can then determine his departure time and route choice effectively in order to minimize his individual total travel cost.

A substantial number of studies have been conducted to model behavior of drivers under ATIS and evaluate system benefit achieved by ATIS, assuming varied type and quality of information, level of market penetration of ATIS and level of traffic congestion.
Mahmassani and Chen (1992) investigated the reliability of the information provided by the ATIS on route choice of commuters. In their study, they proposed two rules for each driver’s path selection and switching. A comparison is also made between the simulation results of adopting pre-trip path information which involves the receiving of information by the drivers while they are using the roads, but there is another type of ATIS called the pre-trip information type. It concerns the provision of traffic information to the commuters before they start their trips on a certain day. This idea was briefly discussed in the study of Srinivasan et al. (1995). On the other hand, there are also some studies involving the analysis of the actual reactions of the drivers towards the ATIS as well as the traffic situation in different aspects such as route choice, acceptance of information (Yang et al., 1993; McCallum and Lee, 1993; Kinghorn et al., 1994; Lerner et al., 1998).

1.5 Objectives of this thesis

This thesis analyses the network reliabilities in two different aspects and thus will be divided into two main parts. As aforementioned, both travel time and capacity reliability are important and useful measures of the performance of a road network. The two reliabilities are essentially interdependent for a given network, but they are so far proposed and modeled separately. It is intriguing to investigate their relationship and how the two complementary reliability measures can be synthesized. For instance, for a given network subject to recurrent or non-recurrent capacity disturbances, travel time or level of service will be different at different levels of demand due to different degrees of flow variation and congestion. However, maximum network flow or capacity will vary at different required levels of service. Thus while a single measure of either travel time or capacity reliability might not be sufficient, their combination may prove to be useful
as a comprehensive performance measure of a road network. Therefore, it would be interesting and meaningful to develop methods for evaluation and integration of road network travel time and capacity reliability. This will constitute a more useful comprehensive performance measure of a road network. This performance measure can be used for robust network planning and design. The objective of the first part of the thesis is to develop methods for the evaluation and synthesis of both travel time and capacity reliability of a road network, thereby forming a comprehensive network performance measure.

The objective of the second part of the thesis is to try to extend the traditional travel time reliability concept by considering both travel time and trip scheduling reliability based on generalized travel cost. This part focuses on a day-to-day analysis of the reliability of commuting time and trip scheduling under ATIS. A simple dynamic traffic network with parallel routes and bottleneck congestion is used to simulate drivers' departure time and route choice decision to minimize total travel time and scheduling delay cost. Accumulated travel experience of drivers and information provided by ATIS are the two major factors in making departure time and route choices.

1.6 The outline of this thesis

Chapter two of this thesis involves the study of integrating travel time and capacity reliability of a road network. Section 2.2 introduces both travel time and capacity reliability of a road network subject to link capacity variations. Section 2.3 investigates the relationship between the capacity and travel time reliability and show how the two concepts can be synthesized to form a more comprehensive network performance measure. A simple analytical example is provided to demonstrate how a two-
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Introduction

dimensional graphical approach can be used to synthesize the two reliabilities.

Discussions will be presented in Section 2.4.

Chapter three of this thesis consists of the analysis of commuting time and trip
scheduling reliability in a simple congested road network under the Advanced Traveler
Information System. The description of the simulation experiment settings in our study
is presented in Section 3.2. Section 3.3 provides the mechanism of driver’s adjustments
of departure time and route choices with information provided. After that, the results of
the experiments are shown in Section 3.4 and discussions are in Section 3.5.

Chapter four of this thesis is the conclusion of the thesis.
CHAPTER 2

INTEGRATING TRAVEL TIME AND CAPACITY RELIABILITY OF A ROAD NETWORK

2.1 Brief description of the study

This chapter proposes to evaluate and synthesize the two interdependent reliabilities of a road network subject to link capacity degradation. A two-dimensional graphical approach is demonstrated to allow for intuitive perception of the changes of the travel time and capacity reliability at varied levels of traffic demand and level of service, thereby leading to a practical and useful reliability-based comprehensive performance measure of a road network.

2.2 Travel time and capacity reliability

2.2.1 Route choice behavior of drivers and road capacity variations

Consider a road network $G(N, A)$ where $N$ is the set of network nodes and $A$ is the set of network links. Congestion effect is considered by using flow-dependent link travel time function $t_a(v_a, c_a), a \in A$ where $v_a$ is the flow on link $a \in A$ and $c_a$ is its capacity. Drivers' route choices are modeled by the following standard user-equilibrium traffic assignment model (e.g., Patriksson, 1994):

$$\min \sum \int_{0}^{v} t_a(\omega, c_a) d\omega$$

(2-1)
subject to:

\[ \sum_{r \in R_w} f'_w = q_w, \quad w \in W \quad (2-2) \]

\[ v_a = \sum_{w \in W} \sum_{r \in R_w} f'_w \delta_{ar}^{w}, \quad a \in A \quad (2-3) \]

\[ f'_w \geq 0, \quad r \in R_w, \quad w \in W \quad (2-4) \]

where \( R \) is the set of routes in the network and \( R_w \) is the set of routes between O-D pair \( w \in W \) and \( W \) is the set of O-D pairs; \( q_w \) is the demand between O-D pair \( w \in W \) and \( f'_w \) is the flow on route \( r \in R \); \( \delta_{ar}^{w} \) equals 1 if route \( r \) between O-D pair \( w \) uses link \( a \) and 0 otherwise. The optimum solution \( f^* = (\ldots, f'_w, \ldots) \) satisfies the following user-equilibrium conditions:

\[ u'_w(f^*) - u_w(f^*) \begin{cases} = 0 & \text{if } f'_w > 0, \\ \geq 0 & \text{if } f'_w = 0. \end{cases} \quad (2-5) \]

where \( u'_w(f^*) = \sum_{a \in A} f'_a (v_a^*) \delta_{ar}^{w} \) is the travel time on path \( r \in R_w \), \( u_w(f^*) = \min\{u'_w(f^*), r \in R_w\} \) is the minimum travel time between O-D pair \( w \in W \). That is, when the travel time on path \( r \) is larger than or equal to the shortest travel time, the flow on that path is zero or the path is not used. When the travel time on path \( r \) is equal to the minimum one, its flow is greater than zero or the path is used.

Clearly, the resultant network travel time and maximum network flow depends on the link capacity: \( c = (\ldots, c_a, \ldots) \). In reality, road capacity is not deterministic, but subject to variations due to traffic accidents, weather conditions, landslides and so on. Let \( c = c_0 - \varepsilon \), where \( c_0 = (\ldots, c_a, \ldots) \) is a vector of normal link capacities and \( \varepsilon \) is a vector of random variables representing link capacity degradation. Variable \( \varepsilon \) may range from
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0 (no degradation) to $c_0$ with complete degradation (or zero capacity). We suppose the probability distribution $p(\varepsilon)$ of occurrence of the perturbation vector $\varepsilon$ is available, which can be estimated from existing sources of data.

Given the fact that link capacities are random variables following a certain probability distribution, we are interested in knowing the resulting probabilistic fluctuations or reliabilities of travel time and maximum network flow through the network.

2.2.2 Travel time reliability of a road network

Travel time is uncertain due to degradable road components and its reliability can be defined as the probability that a trip between an O-D pair can be successfully made within a specified interval of time. Because travel time depends on the degree of congestion, which, in turn, depends on travel demand on the network, its reliability should be defined with respect to a given reference O-D demand pattern. Let $q_0 = (\ldots, q_{w0}, \ldots)$ be a vector of a given basic reference O-D demand pattern (e.g., the current level of O-D demands). To investigate travel time reliability at variable levels of demand, we introduce a factor $\bar{\mu}$ to scale up or down the basic O-D demand pattern uniformly, $q = \bar{\mu}q_0$ and determine the resulting travel time reliability. Let $u_w(c_0, q_0)$ be the travel time between O-D pair $w \in W$ corresponding to the basic reference O-D demand $q_0$ and normal link capacities in a non-degraded state, and let $u_w(c, q)$ be the travel time between O-D pair $w \in W$ corresponding to the multiplied reference O-D demand $\bar{\mu}q_0$ and link capacities in a degraded state. Clearly, $u_w(c, q)$ is a random variable because of random variation of capacity $c$. The travel time reliability under the multiplied O-D demand for an individual O-D pair $w \in W$ is denoted as $TR_w(\pi, \bar{\mu})$ and
defined as the probability of whether the ratio of \( u_w(c,q) \) to \( u_w(c_0,q_0) \) is kept within an acceptable level of threshold \( \bar{\pi} \). Namely,

\[
TR_w(\bar{\pi}, \bar{\mu}) = \Pr \left\{ \frac{u_w(c,q)}{u_w(c_0,q_0)} \leq \bar{\pi} \bigg| q = \bar{\mu}q_0 \right\}, \quad w \in W
\] (2-6)

Clearly, this probability predicts how reliably trips between an O-D pair can be made through a network with degradable links at a certain level of demand. The value \( \bar{\pi} \) can be interpreted as the level of service or travel time threshold that should be maintained.

Note that equation (2-6) is defined with respect to individual O-D pairs and the resulting reliability may vary across O-D pairs. It is sometimes more convenient to use a single index to describe the overall performance of the road network. One possible way to define the overall travel time reliability of the network is to require the travel time ratios between all O-D pairs less than the same common threshold:

\[
TR(\bar{\pi}, \bar{\mu}) = \Pr \left\{ \frac{u_w(c,q)}{u_w(c_0,q_0)} \leq \bar{\pi}, \quad \forall w \in W \bigg| q = \bar{\mu}q_0 \right\}
\] (2-7)

where \( TR(\bar{\pi}, \bar{\mu}) \) is the overall network travel time reliability for prescribed O-D demand level \( \bar{\pi} \) and travel time threshold \( \bar{\mu} \). Note that this might be a conservative measure with a strong requirement and might result in underestimation of the overall network travel time reliability. Nevertheless it can be relaxed by adopting an arithmetic average or demand-weighted average of all O-D travel time reliabilities.
2.2.3 Capacity reliability of a road network

Now we examine the maximum service flow rate and its reliability of a road network. We define the maximum service flow rate as the maximum network flow throughput at a prescribed level of service. For consistence and comparison with the travel time reliability, the level of service is specified as that travel time \( u_w(c,q) \) in a degradable state between each O-D pair should not exceed \( \bar{\pi} \) times the basic reference travel time \( u_w(c_0,q_0) \). Chen et al. (1999) defined the capacity reliability of a network as the probability that the network reserve capacity can accommodate a certain traffic demand at the prescribed service level. Reserve capacity is defined as the largest multiplier \( \mu \) applied to the given basic O-D demand \( q_0 \) that can be allocated to a network without violating the link capacities. Here this definition is slightly modified by adding one additional constraint that the O-D travel time resulting from the equilibrium traffic assignment (2-1)-(2-4) not exceeding the corresponding prescribed travel time threshold:

\[
\max \mu \text{, s.t. } u_w(c,q) \leq \bar{\pi}u_w(c_0,q_0), q_w = \mu q_{w_0}, w \in W, \forall v(c,q) \leq c_v, a \in A \quad (2-8)
\]

Clearly, the largest O-D matrix multiplier \( \mu \) depends on link capacities \( c \). Instead of finding the maximum \( \mu \) with deterministic link capacities \( c_0 \), we are interested in the probability that the network reserve capacity \( \mu(c) \) with degradable link capacities \( c \) is greater than or equal to the required demand level \( q \) specified by a predetermined demand multiplier \( \bar{\mu} (q = \bar{\mu} q_0) \), when link capacity is subject to random variations. This probability is defined as the overall network capacity reliability \( CR(\bar{\pi},\bar{\mu}) \) and is given below.

\[
CR(\bar{\pi},\bar{\mu}) = \Pr \left\{ \exists r, v(a) \delta_w^* \leq c_v, \forall a, \forall w \left| \frac{u_w(c,q)}{u_w(c_0,q_0)} \leq \bar{\pi}, \forall w \in W, q = \bar{\mu} q_0 \right. \right\} \quad (2-9)
\]
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Note that this definition requires that at least one unsaturated path (a path not including over-saturated links) is available between each O-D pair.

In reality an O-D pair may be operational even some other O-D pairs are over-saturated or blocked. We thus introduce O-D pair specific capacity reliability $CR_w(\bar{\pi}, \bar{\mu})$ as follows:

$$CR_w(\bar{\pi}, \bar{\mu}) = \Pr \left\{ \exists r, v(a) \delta_{vt}^w \leq c_v, \forall a \left\{ \frac{u_v(c, q)}{u_v(c_0, q_0)} \leq \bar{\pi}, q = \bar{\mu} q_0 \right\} , w \in W \right\} (2-10)$$

Thus by varying the values of $\bar{\pi}$ and $\bar{\mu}$, we can predict how reliably a network with degradable links can accommodate various required levels of demand at different required level of service in terms of a travel time threshold.

2.3  Synthesis of travel time and capacity reliability

2.3.1  Interdependence of travel time and capacity reliability

It is interesting to see that the aforementioned travel time reliability $TR(\bar{\pi}, \bar{\mu})$ or $TR_w(\bar{\pi}, \bar{\mu})$ shown in (2-6) and (2-7) and capacity reliability $CR(\bar{\pi}, \bar{\mu})$ or $CR_w(\bar{\pi}, \bar{\mu})$ in (2-9) and (2-10) are intertwined through two intervening reference parameters: travel time threshold $\bar{\pi}$ and traffic demand threshold $\bar{\mu}$. This is not surprising if we recall the definitions of the two reliabilities. Travel time reliability is given as the probability that a trip between an O-D pair can be successfully made within a specific interval of time. Travel time depends on the level of demand due to congestion and thus travel time reliability has to be specified with respect to a specific level of traffic demand. On the other hand, capacity reliability is defined as the probability that the network reserve capacity is greater than or equal to a required demand level at a minimum required level
of service. This required level of service could be selected as a threshold of travel time (or scheduled travel time) between each O-D pair. Therefore, the two reliabilities for a given network are interdependent. Figure 2-1 shows diagrammatically the essential elements of these relationships.

The interdependence of travel time and capacity reliability makes it intriguing to investigate how the two complementary reliabilities will change against varied levels of threshold of travel time and traffic demand in the network, and integrate them to form a new comprehensive network performance index. Here we demonstrate a two-dimensional graphical approach to synthesis of the two reliabilities with a numerical example.

2.3.2 Numerical Simulation Settings

In order to show how to intertwine the two reliabilities, a simple network is tested. Figure 2-2 displays the simplified Tuen Mun Highway network in Hong Kong adopted here. There are totally four nodes and ten links with the following BPR functions as their link performance functions:

\[ t_a = \alpha_a + \beta_a \left( \frac{V_a}{C_a} \right)^{\gamma_a} \]  \hspace{1cm} (2-11)

where \( V_a, \alpha_a, \) and \( C_a \) are the flow, free-flow travel time, and capacity of link \( a, \) respectively. \( \beta_a \) and \( \gamma_a \) are the calibrated parameters of link \( a. \) The values of the link characteristics (free-flow travel time and link capacity) from actual observations are given in Table 2-1. Table 2-2 provides the basic reference O-D demands.

Using the Monte Carlo simulation method, we develop a procedure to estimate the capacity reliability and travel time reliability distribution under different OD demand
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Factors, level of service and also link capacities. The procedure is shown in Figure 2-3.
In our simulation we assume that capacity degradation of each network link is independent and the capacity reduction simply follows uniform distribution between normal and half-normal capacity. For each simulation run, only 25% of network links are subject to degradation.

2.3.3 Simulation results and analysis

Figures 2-4a and 2-4b depict the contours of individual O-D based (with 1→3 as an example) and network based capacity reliability respectively, where the vertical axis is the travel time threshold $\bar{\tau}$ while the horizontal axis is the traffic demand threshold $\bar{\mu}$.
We can see that the contours of both figures are rationally distributed as we expect (note that curve smoothing manipulation is made for the data generated from the simulation). At a particular level of traffic demand, higher capacity reliability can be achieved only at the expense of lower level of service (i.e. higher travel time threshold). On the other hand, higher traffic demand results in lower capacity reliability at the same level of service. This is obvious due to the congestion effect on some links. In addition, from the two figures, we can observe that both O-D based and network-based capacity reliability contours exhibit very similar distribution pattern.

Figures 2-5a and 2-5b portray the contours of O-D based and network based travel time reliability, respectively. Clearly the contours are reasonably distributed. At a particular level of traffic demand, lower level of service (i.e. larger travel time threshold) corresponds to higher travel time reliability; lower traffic demand results in higher travel time reliability at the same level of service. In addition, by comparing Figures 2-5a and
2-5b with Figures 2-4a and 2-4b, we can see that travel time reliability contours (either O-D based or network based) are very close to the counterpart of capacity reliabilities. This closeness or difference may well depend on network structure and O-D demand pattern and many other factors.

Once the contours of the two types of reliabilities are established, a number of potential applications can be considered. Such examples of applications are shown in Figures 2-6a and 2-6b. These figures show the domain of traffic demand and travel time that can be achieved at the required travel time and capacity reliability, either for individual O-D pair or for the whole network. The boundary of the domain provides the trade-off between maximum traffic demand and minimum travel time satisfying the same capacity and travel time reliabilities. Similarly, we can easily identify the travel time and/or capacity reliability that can be achieved for given traffic demand and level of service.

2.4 Discussions

The proposed approach can be extended to incorporate reliability in to network design problems (Yang and Bell, 1998): an issue concerning the optimal expansion of roadway capacities or addition of new links to a network to satisfy requirement for both travel time and capacity reliabilities. In this context, one possible formulation is to maximize the network reserve capacity subject to meeting a pre-specified service standard (e.g., mean travel time) with certain reliability (e.g., the probability of the mean time not exceeding a pre-specified threshold).
Figure 2-1. Interdependence of travel time and capacity reliabilities through two intervening variables: travel time and traffic demand thresholds.
Figure 2-2: The simplified Tuen Mun Network

Table 2-1: Link data of the Tuen Mun Road network

<table>
<thead>
<tr>
<th>Link #</th>
<th>$T_r$ (hr)</th>
<th>Capacity (pcu/hr)</th>
<th>$\alpha$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.090</td>
<td>5175</td>
<td>0.1050</td>
<td>3.5</td>
</tr>
<tr>
<td>2</td>
<td>0.1106</td>
<td>850</td>
<td>0.1408</td>
<td>3.6</td>
</tr>
<tr>
<td>3</td>
<td>0.090</td>
<td>5175</td>
<td>0.1050</td>
<td>3.5</td>
</tr>
<tr>
<td>4</td>
<td>0.0056</td>
<td>730</td>
<td>0.0071</td>
<td>3.6</td>
</tr>
<tr>
<td>5</td>
<td>0.0335</td>
<td>4800</td>
<td>0.0335</td>
<td>3.6</td>
</tr>
<tr>
<td>6</td>
<td>0.1106</td>
<td>850</td>
<td>0.1408</td>
<td>3.6</td>
</tr>
<tr>
<td>7</td>
<td>0.0056</td>
<td>950</td>
<td>0.0071</td>
<td>3.6</td>
</tr>
<tr>
<td>8</td>
<td>0.0767</td>
<td>1000</td>
<td>0.1073</td>
<td>3.6</td>
</tr>
<tr>
<td>9</td>
<td>0.0335</td>
<td>4800</td>
<td>0.0335</td>
<td>3.6</td>
</tr>
<tr>
<td>10</td>
<td>0.0767</td>
<td>1000</td>
<td>0.1073</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Table 2-2. Basic reference O-D matrix for simulation of the Tuen Mun network

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>3</th>
<th>4</th>
<th>Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>110</td>
<td>2476</td>
<td>2586</td>
</tr>
<tr>
<td>3</td>
<td>156</td>
<td>-</td>
<td>63</td>
<td>219</td>
</tr>
<tr>
<td>4</td>
<td>2246</td>
<td>39</td>
<td>-</td>
<td>2285</td>
</tr>
<tr>
<td>Attraction</td>
<td>2402</td>
<td>149</td>
<td>2539</td>
<td>5090</td>
</tr>
</tbody>
</table>
Figure 2-3: Flow chart of Monte Carlo simulation procedure
Figure 2-4a: Contours of individual O-D based capacity reliability (origin 1 to destination 3)
Figure 2-4b: Contours of overall network-based capacity reliability
Figure 2-5a: Contours of individual O-D based travel time reliability

(origin 1 to destination 3)
Figure 2-5b: Contours of overall network-based travel time reliability
Maximum Demand and Minimum Travel Time Achievable for given Travel Time and Capacity Reliability Requirement For O-D pair 1-3

Travel time reliability

Capacity reliability

Figure 2-6a: Example for application of two O-D based reliability contours
Figure 2-6b: Example for application of two network based reliability contours
CHAPTER 3

ANALYSIS OF COMMUTING TIME AND TRIP SCHEDULING RELIABILITY UNDER THE ADVANCED TRAVELER INFORMATION SYSTEM

3.1 Brief description of study

In Chapter 2, travel time reliability of a road network was introduced. One of the assumptions in the simulation discussed in Chapter 2 is user equilibrium. However, in our daily lives, it is not quite possible that every commuter has information about the behaviors of others and thus acts correspondingly to achieve the goal of user equilibrium as discussed in Section 2.2. Therefore, travel time reliability may not be a good choice in analyzing dynamic flow network, and travel cost reliability is relatively more appropriate. Let us consider the morning peak-period commuting problem. Most commuters try to reach their work destination within a particular range of work start times, or in a preferred arrival time window. Meanwhile the road network has a limited capacity that is not able to accommodate all traffic within a particular short time period. Thus traffic congestion occurs and it unavoidably causes some commuters to go through the bottlenecks of limited capacity earlier or later than the time window. In this case, a commuter may have a choice between an on time arrival with a long travel or queuing time, and a late or an early arrival with shorter travel times. The commuter has a tradeoff between travel time and schedule delay. Therefore, the journey time and the resultant travel time reliability may be quite different for a different departure time. Also, a commuter's journey time and its reliability are of different importance with a
different departure time. Thus, the aforementioned travel time reliability is not sufficient to explain the desire to lower the likelihood of arriving at the destination at an inconvenient time. Indeed, the inability of accurately predicting arrival times may be more costly to travelers than the extra travel time due to congested traffic. Commuters will generally modify their departure time schedules or route choices to minimize both the cost of travel time and the costs associated with schedule delay, especially late arrival. Disutility felt by commuters should be included in costs owing to travel time and schedule delay and hence they are regarded as a generalized travel cost. Therefore, in this case it is important to consider the reliability of generalized travel cost. In this chapter, we would like to introduce a concept to investigate performance of a network, travel cost reliability. It is defined as the probability that a trip between an origin-destination (O-D) pair can be completed within a certain generalized travel cost.

3.2 Description of simulation model

3.2.1 Network in the model

In our study, we adopt a simulation approach to analyze the driver’s departure time and route choice behavior in a dynamic road network. Figure 3-1 shows the network, which consists of 4 nodes as well as 4 links. For simplicity, all the traffic links are assumed to have zero travel times on running sections so that all those links can let vehicles pass without causing any travel time except at the bottlenecks near the end of the link. On each traffic link, there is a bottleneck of which the capacity is smaller than the incoming flow rate in the morning peak period, and hence queues may develop. Our simulation tries to capture movements of individual vehicles with a limited sample size of 50 vehicles (without loss of generality, this limited number of vehicles is assumed, one sample vehicle in our simulation could, however, correspond to a group of vehicles
Chapter 3  Commuting Time and Trip Scheduling Reliability

in reality). All vehicles move from the same origin node 1 (residential area) to
destination node 4 (working area). At node 2 and node 3, a vector of two side flows
\( X_j = \{X_1, X_2\} \) is generated. Every day the sample vehicles are loaded into the network
according to their departure times, while the side flows are loaded into the network
according to headways generated with a given probability distribution. To model the
impact of day-to-day traffic flow variation, the total daily side flow is assumed to follow
a Normal distribution.

3.2.2 Basic assumptions

In conducting the simulation, the following assumptions are made.

1. Drivers equipped with an ATIS are provided with both pre-trip (travel time and
   scheduling delay cost on previous day or the current day) and in-vehicle
   (instantaneous or predictive route travel time) information and drivers without
   ATIS decide their route choices and departure times by their own experience
   only. Each driver does not know others' decisions. That is, user equilibrium is
   not assumed.

2. The preferred arrival times for all drivers are assumed to be within the same time
   window. They are assumed to have zero schedule cost if they reach their
   destinations within a given time window, and a loss for both early arrival as well
   as late arrival.

3. All drivers are assumed to choose a departure time and routes aiming at
   minimizing their individual travel time and schedule delay cost.
4. Drivers make their day-to-day departure time and route choice decisions based on their individual accumulated travel experience and travel information provided by ATIS.

5. Bayesian updating is introduced to model the behavior of accumulated experience of commuters. It is assumed that all sample commuters can remember all traveling experience and the importance of each day's experience is equal.

3.2.3 Simulation procedure

Using the simulation approach, we develop a procedure to estimate the travel time and trip schedule reliability under different types of ATIS information. To model drivers' departure time choices, the whole modeling period is divided into a number of small intervals and each driver chooses one interval for their departure on each day. The general procedure is shown in Figure 3-2 and can be described below.

Step 0: Identify the type of traveler information provided by ATIS, input the network and demand data, as well as the characteristic of each driver.

Step 1: Set day number \( \text{DAY} = 1 \).

Step 2: Generate a vector of side flows \( X_j = \{X_1, X_2\} \) and headway distributions.

Step 3: Generate the departure time pattern of all drivers.

Step 4: For drivers departing in each interval, generate their route choices according to a certain learning mechanism based on past experience and the information provided by ATIS (for drivers equipped with ATIS).
Step 5: Collect statistics to calculate travel time and schedule delay cost for drivers departing in each departure time interval.

Step 6: Update each vehicle's departure time on the next day based on their experience and departure time information provided by ATIS.

Step 7: If the proposed simulation horizon is reached (i.e. DAY := MAX_DAY), then stop; otherwise DAY:=DAY+1, go to Step 2.

At Step 4, the Bayesian updating (Ang and Tang, 1990) approach is adopted in calculation of the perceived travel time according to past experience and ATIS information. At the end of each day, the departure time and the corresponding total travel cost (travel time and schedule delay) of each driver is recorded. The updated departure time on the next day is determined by applying a logit model to work out the probabilities of choice of each departure time interval by each individual driver.

3.3 Departure time and route choice

3.3.1 Calculation of route travel time

By the time each driver departs, the ATIS will provide travel time to equipped drivers on each of the two routes at node 1. We consider two types of ATIS information: instantaneous information and predictive information.

In the case with instantaneous information, travel time on a route at time \( t \) is considered to be the sum of the (instantaneous) travel times on different links of that route as computed at time \( t \). Let \( Q_i(t) \) be the queue length (number of vehicles in the queue) at time \( t \) at the bottleneck entrance \( i, i = 1,2,3,4 \). The travel time for a driver joining the queue before bottleneck \( i \) at time \( t \) is \( Q_i(t)/s_i \), where \( s_i \) is the exit capacity of
bottleneck $i$. The instantaneous travel time for a driver arriving at node 1 at time $t$ and following route A is:

$$T_A^l(t) = \frac{Q_1(t)}{s_1} + \frac{Q_2(t)}{s_2}$$  \hspace{1cm} (3-1a)

and similarly for route B:

$$T_B^l(t) = \frac{Q_1(t)}{s_3} + \frac{Q_4(t)}{s_4}$$  \hspace{1cm} (3-1b)

For calculation of predictive travel time on each route, it is recognized that the time to clear bottleneck 2 on route A is not $\frac{Q_2(t)}{s_2}$ (the travel time computed at time $t$), but rather that $Q_2$ has to be computed at time $t + \frac{Q_1(t)}{s_1}$, which represents the arrival time at the second bottleneck of that particular sample vehicle joining the queue of bottleneck 1 at time $t$. This type of information is of course more realistic than the first one since actual expected travel time is informed. Now, in this case, the travel time for a driver arriving at node 1 at time $t$ and following route A is:

$$T_A^p(t) = \frac{Q_1(t)}{s_1} + \frac{Q_2(t + \frac{Q_1(t)}{s_1})}{s_2}$$  \hspace{1cm} (3-2a)

and similarly for route B:

$$T_B^p(t) = \frac{Q_1(t)}{s_3} + \frac{Q_4(t + \frac{Q_3(t)}{s_1})}{s_4}$$  \hspace{1cm} (3-2b)

For those uninformed drivers (without ATIS), they will try to choose the route of which the travel time is perceived to be smaller based on their past experiences. The route travel time updating algorithm is actually considering a conditional probability. With past experiences, we assume that each driver will get the statistics of the travel time from the first day to the last day. On a particular day, if an uninformed driver departs, the corresponding past experience of his or her route choice is then recalled. The mean as well as standard deviation of choosing each route (i.e. route A and route B) is
Chapter 3  Commuting Time and Trip Scheduling Reliability

calculated. The concept of Bayesian updating is applied in this calculation. The Bayesian mean \((\mu^*)\) and standard deviation \((\sigma^*)\) is determined by the following equations:

\[
\mu^* = \frac{\bar{x}^2/(\sigma^2/n)^2 + \mu^2/(\sigma^2)^2}{1/(\sigma^2/n)^2 + 1/(\sigma^2)^2} = \frac{\bar{x}(\sigma^2)^2 + \mu^2(\sigma^2/n)}{(\sigma^2)^2 + (\sigma^2/n)}
\]  
\[\text{Equation 3-3}\]

\[
\sigma^* = \sqrt{\frac{(\sigma^2)^2(\sigma^2/n)}{(\sigma^2)^2 + (\sigma^2/n)}}
\]  
\[\text{Equation 3-4}\]

where \(\mu^*\) and \(\sigma^*\) are the predefined mean and standard deviation of travel time respectively; and \(\bar{x}\) and \(\sigma\) are the mean and standard deviation of travel time accumulated in that particular category in past experience respectively; and \(n\) is the accumulated number of cases fell into that particular category.

From both equations (3-3) and (3-4), we can realize that as past experience accumulates, the influence brought by the predefined mean and standard deviation will become less.

After calculation of Bayesian mean and standard deviation, we would assume that the travel time follows Normal distribution. For each route choice, we can combine the corresponding probability distribution with the cost function of the driver, and the expected travel cost \(EC(i,k)\) caused by choosing the route \(r\) for each driver \(i\) on day \(k\) can be determined by integration:

\[
EC(r,i,k) = \int_r \frac{C(i,k)}{\sqrt{2\pi}} \cdot \exp \left\{ - \frac{(t-T)-\mu^*}{\sigma} \right\} \, dt
\]  
\[\text{Equation 3-5}\]
where $T$ is the departure time of driver $i$ on day $k$, $C(i,k)$ is the cost function of driver $i$ on day $k$, $r$ is the route choice of either A or B. Then a final route choice will be determined by comparing the cost induced. The one with less cost will be chosen.

For drivers equipped with ATIS, we suppose predictive travel information is provided and drivers will follow the advice provided. One can also use the Bayesian updating formula to determine drivers’ perceived travel cost from their past experience and the travel time information provided by ATIS, and then the driver will choose route with less perceived cost.

Note that the network status has to be updated once a route choice is made in order to calculate the predictive travel time. A sample driver is loaded into the network according to his/her departure time. At the same time instant, a check will be performed to see if there are vehicles from side roads or any vehicles arrive at their destinations at the same time instant. In our simulation, the time increment (i.e. $\delta t$) is equal to one second. This means a routine check is performed in every second so that more precise behaviors of the vehicles can be simulated.

3.3.2 Adjustment of day-to-day departure time

Day-to-day departure time and route switching are modeled in, for example, Hu and Mahmassani (1995), Jou nd Mahmassani (1998) and Liu and Mahmassani (1999). In these studies, it is assumed that if travelers are not satisfied with their previous selections, they will either change their routes or departure times or both on next day. The concept of indifference bands is introduced and the decisions of modifications of choices depend on whether the resultant performance of the network is acceptable. This
performance can either be assessed in terms of travel costs or the associated earliness or lateness relative to the preferred arrival time. And the modified departure time is also different for each driver due to individual characteristic.

On a particular day of our simulation, when all sample vehicles have reached their destinations, their travel costs will be calculated and they will make decisions of whether their departure times on next day will change according to their individual experiences. For each sample driver $i$, his travel cost consists of three components, travel time (or waiting time), early arrival schedule delay and late arrival schedule delay. Analytically, travel cost $C(i,k)$ of traveler $i$ on day $k$ is calculated below.

$$C(i,k) = \alpha \cdot (T_{Q})_{i,k} + \delta_{i,k} \cdot \beta \cdot (SDE)_{i,k} + (\delta_{i,k} - 1) \cdot \gamma \cdot (SDL)_{i,k}$$  \hspace{1cm} (3-6)

where $\delta_{i,k}$ is 1 for early arrival and 0 for late arrival, $(T_{Q})_{i,k}$ is the travel time (or queuing time) for driver $i$ on day $k$, $\alpha, \beta$ and $\gamma$ are the parameters representing the unit costs of travel time, early arrival schedule delay and late arrival schedule delay, respectively. The schedule delay for early and late arrival for driver $i$ on day $k$ are respectively given by

$$ (SDE)_{i,k} = PAT^e_i - AT_{i,k} $$ \hspace{1cm} (3-7a)

$$ (SDL)_{i,k} = PAT^l_i - AT_{i,k} $$ \hspace{1cm} (3-7b)

where $AT_{i,k}$ is the actual arrival time of driver $i$ on day $k$, $PAT^e_i$ is the upper limit of the range of preferred arrival time at which early arrival is defined if the arrival time of a driver $i$ is earlier than that time; and $PAT^l_i$ is the lower limit of the range of preferred arrival time at which late arrival is defined if the arrival time of a driver $i$ is later than that time.
A few points should be mentioned here on equations (3-6), (3-7a) and (3-7b). First, in equation (3-6), the parameters should be set in a reasonable way. It is obvious that the value of $\gamma$ must be larger than that of $\beta$ as the late arrival penalty must be larger than the early arrival penalty. Secondly, The lower and upper limits of preferred time, $\text{PAT}_i^e$ and $\text{PAT}_i^l$ define the preferred arrival time window, as shown in Figure 3-3, in which no penalty will be imposed on the punctual drivers.

As aforementioned, a discrete rather than continuous time approach is used to model the impact of pre-trip departure time information and drivers' departure time choice. The range of possible departure times of all drivers is divided into $M$ small time intervals of equal length. We assume that on a specific day each driver tries to choose the departure time such that his expected experienced travel cost will probably be minimized.

Because the actual travel cost for a selected departure time depends on all other drivers' selected departure time, predictive travel costs for all departure time intervals are difficult to calculate (at least at moment no efficient way is found) and thus travel cost information for different departure time on the current day is hardly available from ATIS. Nevertheless, we suppose ATIS can provide the actual travel costs for all departure time intervals on previous day (note that a driver may just know his experienced cost for his selected departure time interval on previous day, and may not be aware of the actual travel costs for other unselected departure time intervals). Based on the historically accumulated travel cost and the newly available actual travel cost on the last day, each driver will form his perceived cost for all departure time intervals on current day. One can again use the Bayesian updating formula to calculate the perceived
cost, here the following linear convex combination formula is used to determine the predicted or perceived travel cost for each departure time interval by each driver.

\[ PC(i,m,k) = (1-\phi)AC(m,k-1) + \phi BC(i,m,k-1) \]  \hspace{1cm} (3-8)

In equation (3-8), \( PC(i,m,k) \) is the perceived cost for departure time interval \( m \) by driver \( i \) on current day \( k \); \( AC(m,k-1) \) is the day \( (k-1) \) or previous day's actual travel costs for departure time interval \( m \) experienced by driver \( i \) or other drivers \( i \); \( BC(i,m,k-1) \) is the Bayesian updated travel cost obtained by historical information from first day to previous day for departure time interval \( m \) for driver \( i \). \( \phi \) can be considered to be an experience factor that reflects the relative importance of the newly available travel information and historical information in forming a driver's current perceived travel cost. When \( \phi = 0.0 \), it means that departure times of commuters equipped with ATIS purely depend on pre-trip information, which only considers average travel cost of previous day in different departure intervals; while \( \phi = 1.0 \) indicates drivers choose their departure times based on their own travel experience. Obviously, commuters with ATIS information chooses their departure times with equal weighting of pre-trip information and their own experience when \( \phi = 0.5 \). To determine the Bayesian updated travel cost \( BC(i,m,k-1) \), we consider the historical information of travel costs owing to different departure times. The range of our predefined probable departure times is divided into a number of intervals, and historical travel costs from first day to previous day are stored in the corresponding departure time interval. For each interval, Bayesian updating is applied to obtain a Bayesian updated travel cost owing to past experiences. Note that equation (3-8) is applied to drivers equipped with ATIS because those drivers are assumed to be informed of the actual
travel costs in all departure time intervals on previous day. If a driver is not equipped with an ATIS, then equation (3-8) is applied for the departure time interval selected by this driver on previous day for calculation of his perceived cost on current day. His or her perceived cost for other departure time intervals on current day will remain to be \( BC(i,m,k-1) \) only.

Once the current perceived costs for all departure time intervals are calculated, a logit model is used to determine the probability of choice of each departure time interval as follows:

\[
P(i,m,k) = \frac{\exp(-\theta PC(i,m,k))}{\sum_n \exp(-\theta PC(i,n,k))}
\]  

(3-9)

where \( \theta \) is a parameter reflecting the impact of the uncertainty of perceived cost on driver's choice of departure time, clearly, as \( \theta \rightarrow +\infty \), driver will choose a departure time interval with least perceived cost. Once the choice probability is ascertained, the actual choice of a driver's departure time interval is generated based the determined probability distribution using Monte Carlo simulation. Once a driver's departure time interval is determined, his or her exact clock departure time is randomly given within the selected interval with a uniform probability distribution.

### 3.4 Results of a numerical example

Based on the algorithm mentioned in the previous section, a simulation experiment is carried out to investigate the travel cost reliability for two types of commuters: one type with predictive ATIS and another type without ATIS.
In our simulation model, the perceived information is provided by ATIS and we adopt $20/hr, $10/hr and $100/hr for $\alpha$, $\beta$ and $\gamma$ respectively. $\mu'$ and $\sigma'$ are equal to 0.5 hr and 0.25 hr respectively. The width of the time window for drivers is equal to 0.1 hr. The departure period is 1.8 hrs for all drivers and it is divided into 108 intervals such that drivers can choose the optimal interval for the departure. (That is, one interval is equal to one minute.) Experience factor, $\theta$, is selected to be 0.5. These parameters control the behavioral response of drivers to current network situation. The capacities of bottlenecks at the end of 4 links are fixed ($s_1 = 300 \text{ veh/hr}, s_2 = 200 \text{ veh/hr}, s_3 = 350 \text{ veh/hr}$ and $s_4 = 250 \text{ veh/hr}$).

Owing to the fact that accumulated traveling experience is one of important factors for both ATIS and non-ATIS (uninformed) commuters, the period within which people get the experience from network is regarded as 'warm up' period. After this period, it is expected that the variation of travel cost should be reduced to a certain level. Figure 3-4 shows the coefficients of variation (COV) of day-to-day average generalized travel cost.

This figure is based on the case without side flow variation and the market penetration of the ATIS is 50%. The points plotted in the figure are the coefficients of variation obtained by taking the mean and standard deviation of the resultant generalized travel costs for the previous ten days for both ATIS and non-ATIS commuters. That is, interval 1 takes into account the travel statistics from Day 1 to Day 10 in our simulation and interval 2 considers the travel statistics of the next ten days from Day 11 to Day 20 in our simulation and so on. In this figure, for the first 60 simulation days, the COVs for both ATIS commuters as well as non-ATIS commuters decrease to about 0.1. After 60 simulation days, the values of COVs of two types of commuters seem to become
more stable when they obtain more travel information. From the figure, the coefficient of variation for the ATIS commuters is smaller than that for the non-ATIS commuters and the trends of both lines become stable within a small range of value. This means the degree of fluctuations of the day-to-day generalized travel cost for the ATIS commuters is much smaller than that of the non-ATIS commuters. One reason for this is that the information given by the ATIS is more reliable than the commuters’ individual past experience. Since the ATIS informs the commuters of the current traffic condition of the network, the resulting generalized travel costs perceived by the ATIS commuters will not be subject to large fluctuation from day to day. We believe that the behavioral responses of commuters become stable after 60 simulation days in the case without side flow variation.

Because of congested road network we consider, the capacity of network cannot fulfill the punctual arrivals of all commuters. That is, commuters have tradeoff between travel time and schedule delay. Figures 3-5a and 3-5b show the distributions of the arrival pattern of the commuters over different arrival intervals in the case without side flow variation and the case with a side flow variation respectively. The time interval [30,36] implies the range of the punctual arrival time window in our simulation. Due to our assumption aforementioned, it is impossible for all commuters to arrive at their destinations within the time window on any day (Actually, there is about 65% of commuters who can arrive on time in this experiment.), the commuters need to compete among themselves with a view to minimize their travel costs. Both early arrivals and late arrivals can be observed. In Figure 3-5a, the ATIS commuters, in an overall extent, arrive earlier than the non-ATIS commuters. Apart from that, the number of early arrivals for the ATIS commuters is more than that of late arrivals. However, the
opposite situation is found for the non-ATIS commuters. The reason is that even ATIS commuters and non-ATIS commuters depart at the same departure interval, the chance of arriving earlier for ATIS commuters is greater than for non-ATIS commuters owning to extra ATIS information provided for route choice. The same observation of the behaviors for both ATIS and non-ATIS commuters is also obtained in Figure 3-5b. By comparing both figures, the peaks of the distributions for both commuters in Figure 3-5a are higher than those in Figure 3-5b. Besides, the deviations of the distributions shown in Figure 3-5b are greater than those in Figure 3-5a. That means the arrivals of the commuters when subjected to side flow variation in their daily travel activities spread over a wider range of time intervals. The differences in both figures are due to the side flow variation. In the case of existence of side flow variation, this uncertainty, on the average, induces an extra travel costs for all commuters, so they cannot estimate their travel time so accurately comparing with the case without side flow variation. As a result, there are fewer commuters who arrive at their destinations within the time window and perceive no schedule delay costs in Figure 3-5b and Figure 3-5a represents a better network performance than that implied by Figure 3-5b in terms of punctual arrivals.

Figure 3-6a shows the travel cost reliability contours for the ATIS commuters for different market penetrations of ATIS commuters in the network. The value of market penetration of ATIS commuters means the proportion of commuters equipped with ATIS. That is, the greater this value, the more ATIS commuters in the system. However, the more commuters using ATIS do not mean that the performance of the whole system would be improved. From Figure 3-6a, it is observed that when the market penetration increases, the reliability of travel cost of ATIS commuters steadily
Chapter 3  Commuting Time and Trip Scheduling Reliability

decreases and the travel cost generally increases. The reason is obviously due to an occurrence of over-reaction to the information provided by ATIS. As shown in this figure, the resultant probability of having generalized travel cost less than a particular value will become lower with increasing ATIS market penetration.

From Figure 3-6b, it seems that, for non-ATIS commuters, the increase in the ATIS market penetration does not affect their resulting travel cost reliabilities so much as ATIS commuters. The main reason is that the route choices of the non-ATIS commuters are based on their past experience while those of the ATIS commuters are based on the ATIS route guidance only.

Figures 3-6a and 3-6b show the travel cost reliability contours of ATIS commuters and non-ATIS commuters. It is reminded that travel cost reliability is not defined at zero percent market penetration for ATIS commuters while is also not defined at 100% market penetration for non-ATIS commuters. It is obvious that the performance of ATIS commuters is much better than non-ATIS commuters according to their travel cost reliabilities. For example, to obtain travel cost reliability equal to about 0.8 at 50% market penetration, the generalized travel cost for ATIS commuters is $0.9 while the range for non-ATIS commuters is about $1.8. It depicts the travel cost reliability can be improved by equipping ATIS. Another observation is that the contours in Figure 3-6a seem to be more closely separated than those in Figure 3-6b. The gap among contours in Figure 3-6a is much narrower than in Figure 3-6b. The travel cost reliability of the ATIS commuters can be greatly improved by a small incremental increase in the acceptable generalised travel cost. For the non-ATIS commuters, however, their probability contours are widely separated. Thus, for the same incremental increase in
the acceptable generalized travel cost, the corresponding improvement in their travel
cost reliabilities is not keen when comparing with those of the ATIS commuters

Figure 3-6c shows the travel cost reliability contours for both ATIS and non-ATIS
commuters involved in our simulation. In this figure, we can see when the market
penetration of ATIS commuters equals 0.0, it means that no commuter is equipped with
ATIS whereas when the market penetration of ATIS commuters equals to 1.0, all
commuters in the simulation use ATIS for selecting their departure times and routes.
When the ATIS market penetration is small, the gaps among the contours are large;
when the ATIS market penetration increases, the gaps among the contours gradually
become narrow. This figure shows the inter-relationship between the generalized travel
cost and the market penetration in the whole system, and it is useful for traffic engineers
to design an optimal market penetration based on other criteria such as financial budget
and required network performance.

Figures 3-7a, 3-7b, and 3-7c show the same details as those shown in Figures 3-6a, 3-6b
and 3-6c respectively except that there exists a side flow variation in the simulation.
Side flows from node 2 and node 3 vary with a normal distribution with mean equal to
280 veh/hr and 180 veh/hr and the coefficients of variation are equal to 0.25 for both
nodes. Due to the fact that side flow variation is an uncertainty, with the various day-to-
day side flows, the performance of ATIS commuters in the case without a side flow
variation is better than that in the case with a side flow variation. Side flow variation
mainly influences commuters to predict departure times. Nevertheless, ATIS
commuters can still get the current information for selecting their routes.
Chapter 3  Commuting Time and Trip Scheduling Reliability

Similarly, travel performance of the non-ATIS commuters in the case with side flow variations is worse than that in the case without side flow variations. This is because not only the departure time choices of non-ATIS commuters but also their route choices would be influenced by the variation of side flows. In the case without side flow variation, non-ATIS commuters can estimate the value of side flow for both nodes by their own experience. However, their experience is unreliable for making their route choice decisions with existence of side flow variation.

In the overall extent, the general pattern of the reliability contours shown in Figure 3-7c looks similar to that shown in Figure 3-6c. It is expected that the resultant travel cost reliability shown in Figure 3-6c is higher than that shown in Figure 3-7c. Thus the overall performance for all ATIS and non-ATIS commuters in our simulation in the case with constant side flows is better than that in the case with day-to-day side flow variation. It is believed that the side flow variation is one of the factors to influence the performance of system for the same generalized travel cost and a certain market penetration. With higher coefficients of side flow variation, the performance of system would become worse. Notwithstanding, implementation of side flow variation in our simulation model would give more realistic and meaningful results.

3.5 Discussions

Although some interesting results are obtained in the previous section, future research can be continued to expand the modeling efforts undertaken here. Specific extensions include:

- In the simulation, we suppose the pre-trip information includes the previous day's actual travel time for all departure time intervals. It is, however, more
reasonable to have predictive travel time information for all departure time intervals on the current day. This is particularly meaningful when there are side flow variations.

- Owing to the same information received by all commuters equipped with ATIS, over-reaction seems to be unavoidable. Therefore, it is meaningful to design a mechanism for provision of dispersed departure time guidance information to avoid overflow queues at the bottlenecks, meanwhile taking into account driver's compliance with ATIS advice.

- In our model, choosing routes and departure times are two independent events for all commuters. In reality, these two events should not be independent. Commuters usually have decision which route they use when they depart. Therefore, the proposed new model can be considered to combine them together.
Figure 3-1: Sample network in the simulation
Figure 3-2: Flow chart of simulation procedure
Figure 3-3: Characteristics of the sample vehicles (i.e. loss induced due to different arrival time)

Figure 3-4 - COV of Day-to-day average generalised travel cost

COV

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7

ATIS EXP

Time Interval (one interval = 10 days)
Figure 3-5a - Distribution of drivers in different arrival intervals without side flow variation

Figure 5b - Distribution of drivers in different arrival intervals with side flow variation
Figure 3-6a - Travel cost reliability contours for commuters equipped with ATIS
(the case without side flow variation)
Figure 3-6b - Travel cost reliability contours for commuters without equipped with ATIS (the case without side flow variation)
Figure 3-6c - Travel cost reliability contours for all commuters in the simulation (the case without side flow variation)
Figure 3-7b - Travel cost reliability contours for commuters without equipped with ATIS
(the case with side flow variation)
Figure 3-7c - Travel cost reliability contours for all commuters in the simulation
(the case with side flow variation)
CHAPTER 4

CONCLUSION

Travel time reliability and capacity reliability are studied and integrated as a useful comprehensive performance measure of a road network for a wide variety of traffic flow conditions. For a given network subject to link capacity variations, both reliabilities are investigated in a two-dimensional traffic demand and service level space and represented by iso-reliability contours. Our graphical representation allows for intuitive perception of how, and under what circumstances, a required level of travel time and capacity reliability can be achieved. Therefore, our modeling approach established an efficient procedure for a reliability-based comprehensive performance assessment of a road network.

Travel time reliability is an important measure of a road network especially when describing the performance of network infrastructures by considering travel time of drivers only. However, travel time is not the only factor that commuters consider. Usually, commuters consider their total utility of traveling instead of travel time only. Travel cost reliability is an additional performance indicator of a road network. Travel cost reliability considers both network uncertainties and behavioral responses of road users.

For a given network subjected to a heavily traffic congestion and side flow variation, ATIS is introduced to improve travel cost reliability. It is proved that the performance
of commuters is much better when they equip with ATIS. It is useful especially when there exist uncertainties in the road network. However, the results of our simulation depict that although ATIS can improve the network performance, the benefits to informed commuters decrease with increasing market penetration. Nevertheless, a two-dimensional travel cost and ATIS market penetration are represented by iso-reliability contours. Our graphical representation allows for intuitive perception of the ATIS market penetration at which a required travel cost reliability can be achieved. Our approach established as efficient procedure for reliability-based comprehensive performance assessment of a road network.
REFERENCES


References


References


