Utilizing A Real Life Data Warehouse To Develop Freeway Travel Time Reliability Stochastic Models

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UTILIZING A REAL LIFE DATA WAREHOUSE TO DEVELOP FREEWAY TRAVEL TIME RELIABILITY STOCHASTIC MODELS

by

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A dissertation submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in the Department of Civil and Environmental Engineering in the College of Engineering and Computer Science at the University of Central Florida Orlando, Florida

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ABSTRACT

During the 20th century, transportation programs were focused on the development of the basic infrastructure for the transportation networks. In the 21st century, the focus has shifted to management and operations of these networks. Transportation network reliability measure plays an important role in judging the performance of the transportation system and in evaluating the impact of new Intelligent Transportation Systems (ITS) deployment.

The measurement of transportation network travel time reliability is imperative for providing travelers with accurate route guidance information. It can be applied to generate the shortest path (or alternative paths) connecting the origins and destinations especially under conditions of varying demands and limited capacities. The measurement of transportation network reliability is a complex issue because it involves both the infrastructure and the behavioral responses of the users. Also, this subject is challenging because there is no single agreed-upon reliability measure.

This dissertation developed a new method for estimating the effect of travel demand variation and link capacity degradation on the reliability of a roadway network. The method is applied to a hypothetical roadway network and the results show that both travel time reliability and capacity reliability are consistent measures for reliability of the road network,
but each may have a different use. The capacity reliability measure is of special interest to transportation network planners and engineers because it addresses the issue of whether the available network capacity relative to the present or forecast demand is sufficient, whereas travel time reliability is especially interesting for network users. The new travel time reliability method is sensitive to the users’ perspective since it reflects that an increase in segment travel time should always result in less travel time reliability. And, it is an indicator of the operational consistency of a facility over an extended period of time.

This initial theoretical effort and basic research was followed by applying the new method to the I-4 corridor in Orlando, Florida. This dissertation utilized a real life transportation data warehouse to estimate travel time reliability of the I-4 corridor. Four different travel time stochastic models: Weibull, Exponential, Lognormal, and Normal were tested. Lognormal was the best-fit model. Unlike the mechanical equipments, it is unrealistic that any freeway segment can be traversed in zero seconds no matter how fast the vehicles are. So, an adjustment of the developed best-fit statistical model (Lognormal) location parameter was needed to accurately estimate the travel time reliability. The adjusted model can be used to compute and predict travel time reliability of freeway corridors and report this information in real time to the public through traffic management centers.

Compared to existing Florida Method and California Buffer Time Method, the new reliability method showed higher sensitivity to geographical locations, which reflects the level of
congestion and bottlenecks. The major advantages/benefits of this new method to practitioners and researchers over the existing methods are its ability to estimate travel time reliability as a function of departure time, and that it treats travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time. As such, the new method developed in this dissertation could be utilized in transportation planning and freeway operations for estimating the important travel time reliability measure of performance.

Then, the segment length impacts on travel time reliability calculations were investigated utilizing the wealth of data available in the I-4 data warehouse. The developed travel time reliability models showed significant evidence of the relationship between the segment length and the results accuracy. The longer the segment, the less accurate were the travel time reliability estimates. Accordingly, long segments (e.g., 25 miles) are more appropriate for planning purposes as a macroscopic performance measure of the freeway corridor. Short segments (e.g., 5 miles) are more appropriate for the evaluation of freeway operations as a microscopic performance measure.

Further, this dissertation has explored the impact of relaxing an important assumption in reliability analysis: Link independency. In real life, assuming that link failures on a road network are statistically independent is dubious. The failure of a link in one particular area does not necessarily result in the complete failure of the neighboring link, but may lead to
deterioration of its performance. The “Cause-Based Multimode Model” (CBMM) has been used to address link dependency in communication networks. However, the transferability of this model to transportation networks has not been tested and this approach has not been considered before in the calculation of transportation networks’ reliability. This dissertation presented the CBMM and applied it to predict transportation networks’ travel time reliability that an origin demand can reach a specified destination under multimodal dependency link failure conditions.

The new model studied the multi-state system reliability analysis of transportation networks for which one cannot formulate an “all or nothing” type of failure criterion and in which dependent link failures are considered. The results demonstrated that the newly developed method has true potential and can be easily extended to large-scale networks as long as the data is available. More specifically, the analysis of a hypothetical network showed that the dependency assumption is very important to obtain more reasonable travel time reliability estimates of links, paths, and the entire network. The results showed large discrepancy between the dependency and independency analysis scenarios. Realistic scenarios that considered the dependency assumption were on the safe side, this is important for transportation network decision makers. Also, this could aid travelers in making better choices. In contrast, deceptive information caused by the independency assumption could add to the travelers’ anxiety associated with the unknown length of delay. This normally reflects negatively on highway agencies and management of taxpayers’ resources.
IN THE NAME OF GOD, THE MOST COMPASSIONATE, THE
MOST MERCIFUL

To the sole of my late dearest parents Bayoumy and Fatma
Whose constant love, words and prayers guided me in hard times

To my beautiful loving wife Asmaa
Who supported me with her endless love and care

To my fabulous daughters Fatma and Yasmin
I dedicate you my love, you are all that a father could ask for

To my brothers and sisters
Whose made me the person I am and gave me happy memories

To all my family and friends
Who gave me happiness and precious memories through tough moments
First, I thank God for helping me to accomplish this work. I would like to express my deepest gratitude to my committee chair and advisor, Dr. Haitham Al-Deek. His insights, suggestions, criticism, and support contributed to a great extent in the success of this research. I would like also to thank my committee members Dr. Essam Radwan, Dr. Mohammed Abdel-Aty, Dr. Nizam Uddin, Dr. Linda Malone, and Dr. Morgan Wang for serving in my committee. I sincerely thank Dr. Essam Radwan for his constant support since the first day I joined UCF. I would like also to thank URS Corporation staff, Dr. Hugh Miller, Dr. Bill Olsen, Patricia Palumbo, and Masood Mirza for their continuous support.

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<td>AD</td>
<td>Anderson-Darling</td>
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<tr>
<td>ANOVA</td>
<td>Analysis Of Variance</td>
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<td>ASCE</td>
<td>American Society of Civil Engineering</td>
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<td>ATIS</td>
<td>Advanced Traveler Information Systems</td>
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<td>AVI</td>
<td>Automatic Vehicle Identification</td>
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<td>BPR</td>
<td>Bureau of Public Roads</td>
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<td>BT</td>
<td>Buffer Time</td>
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<td>CBMM</td>
<td>Cause-Based Multimode Model</td>
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<td>CFDW(^{(T)})</td>
<td>Central Florida Data Warehouse(^{(T)})</td>
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<td>CMS</td>
<td>Changeable Message Signs</td>
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<td>EBRM</td>
<td>Event-Based Reliability Model</td>
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<td>ECDRF</td>
<td>Empirical Cumulative Distribution Reliability Function</td>
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<td>ETC</td>
<td>Electronic Toll Collection</td>
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<td>FDOT</td>
<td>Florida Department Of Transportation</td>
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<td>Abbreviation</td>
<td>Definition</td>
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<tr>
<td>FTA</td>
<td>Fault Tree Analysis</td>
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<tr>
<td>GoF</td>
<td>Goodness of Fit</td>
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<tr>
<td>ITS</td>
<td>Intelligent Transportation Systems</td>
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<td>J-ITS</td>
<td>Journal of Intelligent Transportation Systems</td>
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<td>JIT</td>
<td>Just-In-Time manufacturing process</td>
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<td>KS</td>
<td>Kolmogorov-Smirnov GoF test</td>
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<td>LOS</td>
<td>Level of Service</td>
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<td>LSM</td>
<td>Least Square Method</td>
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<td>MPO</td>
<td>Metropolitan Planning Organization</td>
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<td>NCHRP</td>
<td>National Cooperative Highway Research Program</td>
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<tr>
<td>PUE</td>
<td>Probabilistic User Equilibrium</td>
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<tr>
<td>RTMC</td>
<td>Regional Traffic Management System</td>
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<tr>
<td>SP</td>
<td>Stated Preference Survey</td>
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<tr>
<td>TMC</td>
<td>Traffic Management Center</td>
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<tr>
<td>TRB</td>
<td>Transportation Research Board</td>
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<td>UCF</td>
<td>University of Central Florida</td>
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CHAPTER 1
INTRODUCTION

Background

State DOTs, MPOs, and others want to include system performance measures that express congestion and mobility in terms that the system traveler can appreciate and understand. The recent research trend is towards measuring of the travel time delay, and travel time reliability. A number of empirical studies have demonstrated that traveler value not only the time it usually takes to complete a trip but also how reliable the travel times are. Moreover, to have an effect on driver’s behavior, traffic information should consist of clear and unambiguous messages based on accurate and reliable information (Lint et al., 2000). “No surprise and reliable travel time” are what the public want because unreliable travel times can have major impacts on the economic efficiency, individuals’ lives, and the efficiency of the transportation system. Thus, reliability of the transportation system is as important as the system efficiency, if not more.
Importance of Transportation Network Reliability Study

Transportation network reliability has emerged as an important issue, which gained considerable interest by planners and engineers in recent years. It has a regional economic impact influencing the efficiency of movement of individuals and goods. The economies in developed countries depend heavily upon their transportation systems, and that dependence is likely to increase, given the increasing trend towards the just-in-time (JIT) manufacturing processes, which has made reliable travel time tremendously important. JIT as a manufacturing process was not refined until the 1970's by Toyota Motors (NCHRP, 2003). JIT is a production system in which both the movement of goods during production and deliveries from suppliers are carefully timed so that at each step of the process the next (usually small) batch arrives for processing just as the proceeding batch is completed. Producing components in several manufacturing plants and bringing them together in one location at the same time to produce the final product can reduce total costs, but requires a controlled environment of travel time. If one component does not arrive due to traffic delays, an assembly line can be slowed or shut down, or costly building space has to be used for inventory storage, rather than for manufacturing or assembly operations. Therefore, JIT highly relies on the transportation system to take advantage of low-cost labor and manufacturing plant development costs.

On the other hand, the traveling public experiences these large performance swings, and their expectation or fear of unreliable traffic conditions affects both their view of roadway
performance, as well as how and when they choose to travel. For example, many commuters will plan their departure times based on an assumed travel time that is greater than the average to account for a lack of reliability. The public are becoming more and more reliability conscious every day as they realize how costly unreliability is becoming in their daily efforts.

Travel choice behavior studies found that travelers rated the transportation system reliability as a highly important feature. For example, an empirical study found that 54% of the respondents in the stated preference (SP) survey indicated that travel time reliability is either the most important or second most important reason for choosing their daily commuter routes (Abdel-Aty et al., 1996). A recent study noticed that people place a cost not only on the average travel time, but also on its variance. Travelers were found to put a cost of $2.6 to $8 per hour of the mean, and $10 to $15 per hour of the standard deviation of travel time (Chen et al., 2003).

Apart from the effect on normal day-to-day life, transport systems are an important lifeline in the event of a natural disaster; snowfall, floods, landslide, earthquake, and hurricane. Other lifelines (electricity, water supply, and communication networks) can be restored in a relatively short period of time. The restoration of these systems depends on accessibility to the damage sites or in other words the reliability of the transportation network (Du and Nicholson, 1997).
For the above reasons, considerable attention has been devoted toward the development of methods that can be used to estimate the reliability of transportation networks in terms of travel time reliability and capacity reliability measures. However, before taking the study of reliability any further, precise definitions are required from the transportation standpoint. The transportation profession is still developing many of its fundamental principles. In addition, practitioners are not well versed in data and methods to measure travel time reliability (NCHRP, 2003). A definition of the reliability in general and travel time and capacity reliabilities in particular are crucial for the development of this research.

### Network Reliability Measures

Network reliability theory has been applied extensively in many real-world systems such as computer and communication systems, power transmission and distribution systems. In this context reliability is defined as “the probability that an entity will perform its intended function(s) satisfactory or without failure for a specified length of time under the stated operating conditions at a given level of confidence” (Kececioglu 1991; and Tobias and Trindade, 1995). The term ‘entity’ is used here to denote any component, product, subsystem or system that can be individually considered and tested separately. A ‘function’ is defined as a function, or combination of functions of an entity, which is necessary to provide a given service.
The reliability (R) as a probability ranged from R = 1 (perfect reliability or 0% probability to failure) to R = 0 (Complete unreliability or 100% probability to failure). In the mathematical sense (Villemerur, 1992), reliability is generally measured by the probability that an entity can perform adequately under given conditions for a given time interval [0, t]. Although this definition is simple, the notion can be applied to complex systems.

In transportation systems, network reliability means in general the reliability of its connectivity, capacity, and/or travel time (Chen et al., 1999), as will be explained in details later. The analysis of network reliability involves measuring the ability of the network to meet some expected functional criteria or “tolerance” set by its travelers, which in turn varies according to the severity and frequency of the underlying ‘non-recurrent’ and ‘recurrent’ causes.

Connectivity reliability is the probability that network nodes are connected. The network is considered successful if at least one path (set of links) is operational. The binary state approach limits its application to everyday situations. Consequently, the connectivity reliability is not a sufficient measure and the results obtained through this approach may be misleading for normal conditions and even under emergency conditions (Chen and Recker, 2000).
Subsequent research was directed at degraded networks, usually urban road networks subject to traffic congestion (recurrent and non-recurrent), in which the network remained physically intact but the performance of one or more of its links could be severely affected by congestion. These measures consider the quality of service and daily fluctuations, which connectivity reliability does not consider. This led to the definition of the other two additional forms of reliability: capacity reliability, and travel time reliability.

Capacity reliability explicitly considers the uncertainties associated with capacities by treating roadway capacities as continuous quantities subject to degradation due to physical and operational factors. For example, it is defined as the probability that the maximum network capacity is greater than or equal to a required demand level when the link capacity is subject to random variations or capacity degradation (Chen et al., 2002). For more detailed description of computing capacity reliability, refer to (Chapter 3).

Travel time reliability subject is challenging because there is no single agreed-upon travel time reliability measure. Different researchers have used different definitions of transportation network travel time reliability. For example, travel time reliability is defined as the probability that a trip can be made within a specific duration of time or alternatively, just a percentile of travel times (Levinson and Zhang, 2001). Additionally, the following definitions of reliability have been documented in previous literature (Chen et al., 2003; Levinson and Zhang, 2001; and Shaw and Jackson, 2003):
• Ability of travelers to predict travel time for a trip and to arrive at destination within an “on-time window”, measured by how travel time of a trip varies from one time period to another.

• The variability of travel times “How long will a trip take today compared to the same trip at the same time on any average day?”

In this research, a new method for estimating travel time reliability is developed. The new method’s definition of travel time reliability is totally different from the existing methods. This definition is well demonstrated in Chapters 3, 4 and 5. Unlike the existing methods that defined reliability in terms of travel time variability, the definition of reliability in the new method places more emphasis on the traveler’s perspective. The new method would have the potential ability to estimate travel time reliability as a function of departure time by treating travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time.

**Problem Description**

Based on the literature review introduced in this dissertation, it was concluded that there is a clear need to develop a comprehensive methodology for reliability analysis where demand exceeds capacity on different links (not just in cases of complete failure) and comparison between capacity reliability and travel time reliability measures for the same network to find
out which is more appropriate to be used as a new performance measure to evaluate the freeway operations.

By tracking the travel time reliability measures that have been used in the U.S., the Buffer Time Method and Florida Reliability Method rise above others as the preferred measures, and they seem to resonate with most audiences. However, for these measures, it is not certain what level of reliability (e.g., 85%, 90%, or 95%) should be used. Also, previous studies assumed Weibull and Normal distributions for travel time reliability but this assumption was never verified with real life travel time data. This has a direct impact on the accuracy of predicting reliability.

Furthermore, none of the previous studies compared between the most commonly used methods using real life data. And none of these existing methods considered the impact of segment length on travel time reliability estimation. As such, the main goal of this research is to develop a methodology that will address these major shortcomings.

The literature review showed also that previous studies assumed that link failures in a road network are statistically independent. In real life, this assumption is dubious, since the failure of a link in one particular area does not necessarily result in the complete failure of the neighboring link, but may lead to deterioration of its performance. Based on the
methodological review introduced in this dissertation, it was undoubtedly concluded that the literature is in need to a new methodology that can account for multimodal dependency link failure conditions, which have not been considered before in the calculation of transportation networks’ reliability. The new developed methodology would take into consideration that, the main mechanism that defines the state of the network is the interaction between demand and supply. The network supply interacts with various external factors, such as incidents, work zones, weather conditions or natural/manmade disasters, which can cause degradation in the network performance by reducing its link capacities (non-recurrent causes). Also, the demand fluctuates, sometimes due to special events, or within the day and/or between days.

References


As discussed earlier, the travel time reliability measure is important for both planning future improvements and evaluating current deployments because the successful wide scale deployment of Advanced Traveler Information Services (ATIS) depends on the ability to obtain and subsequently disseminate reliable information that accurately reflects network traffic conditions. In addition, this measure can help travelers and freight companies make planning and scheduling decisions of their trips. As a result, the main goal of this research is to investigate and develop a new methodology to calculate travel time reliability measure. This includes testing the transferability of a wide range of the well-known engineering reliability techniques (e.g., borrowed from communication networks) to the transportation field. Specific objectives of this research are listed in the following subsection.

Research Goal and Objectives

The main goal of this dissertation is to come up with a new method for estimating travel time reliability in transportation networks that address shortcomings of existing methods. Specific
objectives of this research include: (1) Modeling travel time reliability as a new measure of performance as continues variable; (2) Examining new statistical stochastic models such as: Weibull, Exponential, Normal, and Lognormal to model link travel time reliability; and (3) Presenting and applying the “Cause-Based Multimode Model” (CBMM) to predict transportation networks’ travel time reliability under multimodal dependency link failure conditions which have not been considered before in the calculation of transportation networks’ reliability. The analysis framework and evaluation approaches to accomplish the main goal and specific objectives of this research are as follows.

- **Key Assumptions**
  1. Improved knowledge of travel time conditions will result in better operational and planning strategies.
  2. Travelers will react positively to information on alternate routes.
  3. Travel time information will be accurate.

- **Specific Data Needs (Data Sources)**
  1. Hypothetical network:
     - Links’ travel time, traffic flow and capacity, (Chapters 3 and 6).
     - Capacity degradation events (links’ failure causes and probabilities), (Chapter 6).
     - Probabilities of causes’ effects on each link, (Chapter 6).
  2. Freeway corridor (I-4 eastbound):
     - Dual loop detectors’ locations and spot speeds, (Chapters 4 and 5).
– Segments’ origins, destinations and speed limits, (Chapters 4 and 5).
– Corridor elements’ locations (e.g., freeway ramps), (Chapters 4 and 5).

• **Analysis Methods**

1. Develop new definitions of travel time reliability as well as capacity reliability of transportation networks, (Chapter 3).

2. Develop a comprehensive methodology for reliability analysis where demand exceeds capacity on different links, not just in the cases of complete failure, (Chapter 3).

3. Apply the new method to estimate the effect of travel demand variation and link capacity degradation on the expected travel time and capacity reliabilities of a roadway network, (Chapter 3).

4. Compare the capacity reliability measure to the travel time reliability, (Chapter 3).

5. Utilize the wealth of data available in the I-4 corridor data warehouse in Orlando, Florida to test the transferability of reliability techniques in the transportation field, (Chapters 4 and 5).

6. Define the appropriate evaluation criteria to compare between the four proposed stochastic models: Weibull, Exponential, Normal, and Lognormal (Chapters 4 and 5).

7. Compare the existing Florida and Buffer Time methods to the new reliability method, (Chapters 4 and 5).
8. Investigate the impact of segment length on the accuracy of calculated travel time reliability, (Chapter 5).

9. Present and apply the “Cause-Based Multimode Model” to predict transportation networks’ travel time reliability under multimodal dependency link failure conditions, (Chapter 6).

10. Model travel time reliability of multi-state independency link failures, (Chapter 6).

11. Model travel time reliability of multi-state dependency link failures, (Chapter 6).

12. Compare the dependency and independency analysis scenarios, (Chapter 6).

**Research Conceptual Plan**

After conducting a thorough literature review it became obvious that there is a need to develop a new methodology for modeling travel time reliability which utilizes the massive traffic data available in freeway data warehouses. Figure 2.1 shows the conceptual plan for modeling freeway travel time reliability. An “experimental design” was developed to find the best-fit travel time stochastic model (Weibull, Exponential, Lognormal, and Normal). *Anderson-Darling* (AD) and the 95th percentile of the absolute errors as two evaluation criteria were selected to check the validity of our assumptions regarding the specific stochastic model parameters. Unlike the mechanical components, travel time on freeway segments cannot be zero. Accordingly, an adjustment of the best-fit stochastic model
location parameter was needed. Next, if the calculated travel time for a specific segment on a specific day would be less than the acceptable travel time, then the segment would be considered 100% reliable. In this paper, the acceptable travel time is defined as travel time at speed limit. Otherwise, the developed reliability stochastic models would be used to calculate the segment/corridor travel time reliability for a specific departure time. The new method results are compared with existing FDOT and Buffer Time methods. The travel time reliability estimates could be disseminated in real time to public via advanced traveler information systems to help in pre-trip planning and/or en-route diversion.
Figure 2.1: Research conceptual plan
Research Organization

This dissertation is organized into seven chapters. A brief summary of the main contents of the seven chapters is shown below.

Chapter One, Introduction, provides an introduction to the research topic, importance of the transportation network reliability study, and the existing definitions of reliability. Chapter Two, Research Framework, presents the research main goal and specific objectives. Chapter three, J-ITS Paper, presents a paper accepted for publication in the Journal of Intelligent Transportation Systems (J-ITS). In this paper, a new method is presented for estimating the effect of travel demand variation and link capacity degradation on the expected reliability of a roadway network, and a comparison between the travel time reliability and capacity reliability measures. Chapter Four, TRB Paper, presents a paper accepted for publication in the Transportation Research Record: Journal of the Transportation Research Board. This paper shows the utilization of a real life transportation data warehouse to develop a new methodology for estimating travel time reliability of the I-4 corridor in Orlando, Florida, and the comparison between the existing Florida and Buffer Time methods and the new reliability method. Chapter Four, J-ITS Paper, presents a paper to be submitted to the Journal of Intelligent Transportation Systems (J-ITS). It shows the utilization of a large data set available in the I-4 data warehouse, and investigates the impact
of segment length on the accuracy of travel time reliability calculations. *Chapter Five, ASCE Paper*, presents a paper accepted for publication in the American Society of Civil Engineering: Journal of Computing in Civil Engineering. The paper presents a new methodology to study the multi-state system reliability analysis of transportation networks for which one cannot formulate an “all or nothing” type of failure criterion and in which dependent link failures are considered. The paper compares between the dependency and independency analysis scenarios and results. *Chapter Seven, Conclusions, Recommendations, and Future Research* summarizes the conclusions and contributions of this dissertation and recommendations for future research.
CHAPTER 3
NEW METHODOLOGY FOR ESTIMATING RELIABILITY IN TRANSPORTATION NETWORKS WITH DEGRADED LINK CAPACITIES

Abstract

The measurement of transportation network reliability is a complex issue because it involves both the infrastructure and the behavioral responses of the users. This subject is challenging because there is no single agreed-upon reliability measure. Sources of system unreliability include natural and man-made disasters, recurrent events that result from demand variation, and non-recurrent events that affect network supply such as incidents, work zones, and weather conditions. This paper introduces a new method for estimating the effect of travel demand variation and link capacity degradation on the expected reliability of a roadway network. The method is applied to a roadway network and results of travel time reliability and capacity reliability are presented. The new travel time reliability method is sensitive to the users’ perspective since it reflects that an increase in segment travel time should always result in less travel time reliability.
Reliability engineering is a well-established area. Reliability theory has been widely associated with the design and management of communication and computer networks and the performance of mechanical equipment. In this context, reliability is defined as “the probability that components, products or systems will perform their intended functions without failure for a specified length of time under the stated operating conditions at a given level of confidence” (Kececioglu 1991). In transportation systems, network reliability has emerged as an important issue which gained considerable interest by planners and engineers in recent years.

Travel choice behavior studies found that users rated the transportation system reliability as a highly important feature. For example, an empirical study found that 54% of the respondents in the stated preference (SP) survey indicated that travel time reliability is either the most important or second most important reason for choosing their daily commuter routes (Abdel-Aty et al. 1996). Also, Chen et al. (2003) noticed that people place a cost not only on the average travel time, but also on its variance. Travelers were found to put a cost of $2.6 to $8 per hour of the mean, and $10 to $15 per hour of the standard deviation of travel time. Recently, Bonsall (2004) found that the actual choice depended not only on the consequences of arriving at different times but also on the traveler’s perception of the probabilities involved and his or her attitude to risk. The consequences of an unexpected delay during a journey
would probably be insignificant if the time could be made up later in the journey, but could be serious if the traveler was already late for an appointment.

Travel time reliability has a regional economic impact influencing the efficiency of movement of individuals and goods. Reliable travel time information enables travelers to make better travel choices, and reduces their level of anxiety (due to stress of the unknown) when traveling under recurring and non-recurring congestion conditions. On the other hand, when travel information is unreliable or unavailable, travelers tend to lose confidence in the transportation system and this reflects negatively on public agencies running the transportation system. Unreliability adds uncertainty to freight delivery which often translates into overtime payments to truck drivers who are stuck in traffic. To avoid this problem, freight companies schedule excess time in each delivery to account for traffic delays. This results in higher costs to customers.

Apart from the effect on normal day-to-day life, transportation systems are an important lifeline in the event of a natural or man-made disaster, e.g. floods, earthquakes, hurricanes, and bomb explosions. The transportation network provides access to emergency services, aid workers and relief supplies. In addition, other lifelines (electricity, water supply, and communication networks) can be restored quickly if transportation access to damaged sites is fast and reliable (Du and Nicholson 1997).
In this paper, a new method is developed to calculate both travel time reliability and capacity reliability of a transportation network under degraded link capacity. It is important to emphasize that the developed methodology can be extended to communication networks, in the field of electrical engineering, as well as infrastructure networks or infrastructure elements such as bridges and tunnels. For example, a communication network consists of a set of nodes representing communication centers and a set of edges representing links between the communication centers. Unrestricted edges are used to represent two-way communication links between two nodes. The new developed methodology could be used to calculate the traffic delay (i.e., messages) and compare it to an acceptable value for the network traffic delay, then calculate the probability that the network would satisfy the requirements for traffic delay (not to exceed a predefined threshold).

Also, we provide a review of the state of the art in the field of transportation network reliability and an overview of travel time reliability measures that have been utilized by various transportation agencies across the U.S. Finally, we present a new method for estimating the reliability of a roadway system with an illustrative network example.

**An Overview of Network Reliability Analysis**

Travel time is one of the most important measures of transportation network performance. Other measures such as fuel consumption, vehicle emissions, and accidents are related to
travel time. The traditional methods of reporting travel time experienced by travelers consider only “average” or “typical” conditions. However, continuous variations in roadway environment cause travel times to vary on the same facility during the same time period. The transportation network can be viewed as a system with multiple states and each state is defined by the interaction mechanism between supply and demand (NCHRP 2003). The network supply interacts with various external factors, such as incidents, construction work zones, weather conditions and natural/manmade disasters, which can cause degradation of the network performance by reducing its link capacities. Also, the demand fluctuates, sometimes due to special events, or within the day and/or between days. These variations lead to a variable service state of the network and unreliable travel times.

A state of the network is fully described by the modes in which all of its links are operating. For illustration, each link in the network may be assumed to have various degraded modes based on the level of congestion (represented by the flow and capacity ratio, v/c ratio). For example, the following modes could be assumed: moderate congestion (mode 0 or up mode), heavy congestion (mode 1 or degraded mode), and severe congestion (mode 2 or jam mode) with (v/c) ratios 0.9, 1.2, and 1.5 respectively. The state of the network is a combination of its links’ modes. Accordingly, for a network with 5 links, one of its states could be (1, 0, 2, 1, 0) which means that Links 1 and 4 are in the moderate mode (v/c = 1.2), Links 2 and 5 are in the up mode (v/c = 0.9), and Link 3 is in the jam mode (v/c = 1.5). More details are provided under the numerical example section.
Network Reliability Measures

Network reliability has been the subject of considerable international research interest (e.g., see Bell and Cassir, 2000 and Bell and Iida, 2003). Much of this research has focused on congested urban road networks and the probability that the network will deliver a required standard of performance.

In general, network reliability means reliability of its connectivity, capacity, and/or travel time (Chen et al., 1999). These are explained below. The analysis of network reliability involves measuring the ability of the network to meet some expected functional criteria or “tolerance” set by its users, which in turn varies according to the severity and frequency of the underlying ‘non-recurrent’ and ‘recurrent’ causes.

Recurrent congestion is generally characterized by everyday rush-hour stop and go conditions, occurring when demand exceeds capacity. Non-recurrent congestion is caused by incidents, maintenance work or construction activities where normal capacity is temporarily reduced and special events where peak demands are higher than normal.

In the case of non-recurrent congestion, Iida et al. (2000) presents a useful classification of the various network states of functional expectation following a major earthquake. The first period is the ‘confusion state’, where the main reliability index considered is connectivity reliability, which is defined as “the probability that the network nodes remain connected”.

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The second state is the ‘recovering period state’, where the demand pattern continuously adjusts itself back to ‘normal’ level, but the network is still seriously degraded. The third and final state is the ‘stability state’, where demand patterns have reached their normal level, and the reliability analysis returns to that made for recurrent causes. In this case, the immediate impact on travelers is experienced in terms of the variability in travel times. The most common three reliability measures for road networks are summarized below (Chen et al. 1999).

**Connectivity Reliability**

This is used as a measure of the probability that network nodes are connected. The network is considered successful if at least one path is operational. A path consists of a set of links, which are characterized by zero or one to denote the link’s status (operating or failing). This binary approach has limited applications to everyday situations where roadway links are operating in-between the two extremes, but it may be suitable for abnormal situations such as earthquakes (Iida and Wakabayashi 1989; Asakura et al. 2001; and Kurauchi et al. 2004). Wakabayashi (2004) found that network connectivity reliability could be improved effectively by improving the most important key link on the network. When such important link is discovered, this enables the improvement and maintenance of network connectivity reliability efficiently.
**Capacity Reliability**

Chen et al. (2002) defined capacity reliability as the probability that the network can accommodate a certain demand at a given service level when the link capacity is subject to random variations. Lo and Tung (2003) calculated the maximum flow a network can accommodate subject to the route choice principle of probabilistic user equilibrium (PUE) under degradable link flow capacities (minor day-to-day events of stochastic link capacity variations). Accordingly, connectivity reliability is a special case of capacity reliability when capacities are assumed to be only discrete binary values (zero for total failure and one for operating at ideal capacity).

Capacities for a road network can change from time to time due to various reasons such as traffic incidents and weather conditions. For example, reductions in road capacity by 10% to 15% had been observed during heavy precipitation (Hoogendoorn and Van 2000). Capacity reliability explicitly considers the uncertainties associated with capacities by treating roadway capacities as continuous quantities subject to routine degradation due to physical and operational factors.

**Travel Time Reliability**

The subject of travel time reliability is challenging because there is no single agreed-upon travel time reliability measure. Different researchers have used different definitions of transportation network travel time reliability. Below, we explain in detail two of the most
commonly used methods of travel time reliability in the US, these are the Florida Reliability method and the California Buffer Time method.

**Florida Reliability Model**

The Florida Reliability Method was derived from the FDOT’s definition of reliability of a highway system as the percent of travel on a corridor that takes no longer than the expected travel time plus a certain acceptable additional time \( TT = X + \Delta \), FDOT 2000. The FDOT method defines an upper threshold and calculates the probability that the actual travel time will be less than this threshold. The percent of reliable travel is calculated as the probability of travel that is acceptable (takes no longer than this acceptable travel time). Mathematically, reliability \( R(t) \) is defined by the Florida method as:

\[
R(t) = P(x < X + \Delta) = P(x < TT)
\]

Where:

\[ X \rightarrow \] The median travel time across the corridor during the period of interest; and

\[ \Delta \rightarrow \] A percentage of the median travel time during the period of interest, percentages of 5%, 10%, 15%, and 20% above the expected travel time have been considered but a decision has not been finalized (FDOT, 2000).

**California Buffer Time Reliability Method**

The buffer time concept may relate particularly well to the way travelers make decisions, it uses minutes of extra travel time needed to allow the traveler to arrive on time (Chen et al.
The buffer time is calculated as the difference between the average travel time and the upper limit of the 95% confidence interval of average travel time. The main problem is that the public does not readily understand the Buffer Time. It is not certain what level of reliability (e.g., 85%, 90%, or 95%) should be used in both the Florida and Buffer Time methods.

Other researchers (Asakura and Kashiwadani 1991; and Levinson and Zhang 2001) defined travel time reliability as the probability that a trip can be made successfully within a specified interval of time. They defined an interval (lower and upper bounds) and calculated the probability that the travel time will be within this interval. Chen & Recker (2000) assumed travel time reliability is a function of the ratio of the travel times under the degraded and non-degraded states.

Previous studies addressed transportation network reliability through, for example, a game theoretic approach (Bell 1999), using stochastic user equilibrium (Asakura 1999), simulating traffic flow (Lam and Xu 1999), measuring capacity of the network (Chen et al. 1999), vulnerability of the network (Lleras and Sanchez-Silva 2001), and stochastic demand (Sumalee and Watling 2004). A recent study (Dalziell and Niclson, 2001) looked at the failure of critical infrastructure components of the network (risk of road closure) in terms of travelers’ disruption to all road users of the studied network and not only the road closure.
Based on the above literature review, there is a clear need to develop a comprehensive methodology for reliability analysis where demand exceeds capacity on different links (not just in the cases of complete failure) and compare between capacity reliability and travel time reliability measures for the same network.

### Reliability Estimation

Most studies on transportation network reliability use Bernoulli random variable (fail/operate). However, for road networks, complete failure is a rare event. A link in a transportation network may be operating at a partially reduced capacity. To model everyday disturbances, one must consider various levels of capacity degradation (Nicholson and Du 1997, and Chen et al., 2002). A reasonable way to capture these variations and their impacts is to model roadway reliability using probability distributions. The following two sections present a new method for determining transportation link and network reliability in the simplest case of independent link failures.

### Link Reliability Analysis

Du and Nicholson (1997) as well as Chen et al., (1999, 2002) formulated reliability as an adequacy problem to determine whether or not the probable network capacity is sufficient to accommodate the required demand. Generally, it is desirable that a transportation network
reliability model be able to handle a range of link degradation levels, where a link is assumed to have multiple states of operation more than just two (operate/fail).

A schematic representation of the capacity and demand functions is shown in Figure 1 (Patrick et al., 2002 and Harr, 1987). If the known capacity exceeds the known demand, as shown in Figure 3.1(a), then failure will not occur (state 0). However, in most cases, there will be some uncertainty about both. The actual capacity and the demand (flow) of any population of components (links) will vary. A schematic representation of the capacity and demand functions as probability distributions is shown in Figure 3.1(b & c). As before, failure will not occur so long as the demand does not exceed the capacity. However, if the maximum demand exceeds the minimum capacity (Figure 3.1c), the distributions will overlap and there will be nonzero probability of failure. It is apparent that the nominal values of both the capacity and the demand cannot be determined with certainty, and hence a particular state of the network is fully described by the states in which all of its links are operating.

**Link Capacity Reliability**

In this paper, capacity reliability is defined as the probability that the demand \( x_i \) is less than the mean link capacity \( \bar{C}_i \) plus an acceptable threshold. The threshold can be expressed as fraction of the mean capacity \( (\varepsilon_i \bar{C}_i) \), where \( 0 \leq \varepsilon_i \leq 1 \). The excess demand over link capacity,
also referred to as tolerance $S_i$ for link $i$, where $(S_i = x_i - C_i)$, is itself a random variable as illustrated in Figure 3.1d. Link capacity and demand are both assumed to have normal distributions based on the study conducted by (Al-Kaisy and Hall, 2000). In this study, it is mentioned that based on normality test of the field observations, it was confirmed that the capacity distribution largely follows the normal curve. Mathematically, any linear combination of two normal variables is also normally distributed. As a result, tolerance has a normal distribution with mean and variance as follows:

$$E(S_i) = E(x_i) - E(C_i) = \left(\bar{x}_i - \bar{C}_i\right)$$

$$\sigma^2[S_i] = \sigma^2[x_i] + \sigma^2[C_i] - 2 \rho \sigma[x_i] \sigma[C_i]$$

Where, $\sigma[x_i]$ and $\sigma[C_i]$ are the standard deviations of the link demand and capacity respectively, and $(\rho)$ is the correlation coefficient between them. The probability of failure (or demand exceeding capacity by more than the acceptable tolerance) can be written as:

$$p(f) = \left[ P\left((x_i - C_i) \geq \varepsilon_i \bar{C}_i\right) \right] \text{ or } p(f) = P\left(S_i \geq \varepsilon_i \bar{C}_i\right)$$

Hence for the assumed normality, we have the simple, but important, relationship for the probability of failure as follows:

$$p(f) = \left[ P\left(S_i \geq \varepsilon_i \bar{C}_i\right) \right] = P\left(\phi_i \geq \frac{\varepsilon_i \bar{C}_i - E(S_i)}{\sigma[S_i]}\right) = 1 - \psi(\phi_i)$$

Where the standard normal distribution function $\psi(\phi_i)$ defines how reliable the existing link is with degradable capacity under a given demand level. The reliability index $(\phi_i)$ is defined as the number of sigma units (the number of standard deviations $\sigma[S_i]$) between the mean
value of the tolerance \((E[S_i] = \bar{S})\) and \((S_i = \varepsilon_i C_i)\). The reliability index can be obtained as:

\[
\phi_i = \frac{\varepsilon_i \bar{C}_i - E(S_i)}{\sigma[S_i]} = \frac{\varepsilon_i \bar{C}_i - \left[\bar{x}_i - \bar{C}_i\right]}{\sqrt{\sigma^2[C_i] + \sigma^2[x_i] - 2 \rho \sigma[C_i] \sigma[x_i]}}
\] (5)

Then, link capacity reliability can be calculated as \((R_i = 1 - P(f) = \psi(\phi_i))\). The \(\psi(\phi)\) values can be obtained from the standard normal distribution table. Furthermore, Equation 5 as well as Figure 3.1e illustrate the dependency of the standard deviations of the tolerance \((\sigma[S_i])\) on the correlation coefficient \((\rho)\) between capacity and demand (Harr, 1987). Correlation is a bivariate measure of association (strength) of the relationship between two variables. It varies from 0 (random relationship) to 1 (perfect linear relationship) or -1 (perfect negative linear relationship). As expected, it is seen that the reliability index is a maximum (Equation 5) for a perfect positive correlation \((\rho = +1)\) and a minimum for a perfect negative correlation \((\rho = -1)\).

Field experiments could be conducted to estimate the correlation between demand and capacity of a roadway network. It has to be noted that the correlation between two variables “i.e., demand and capacity” is defined as the covariance of demand with capacity divided by the product of the standard deviation of demand and the standard deviation of capacity. The covariance is the mean value of all pairs of differences from the mean of demand multiplied by the differences from the mean of capacity. If demand and capacity are not closely related
then the covariance is small and the correlation is small. If demand and capacity are closely
related, then covariance will be close to the product of demand and capacity’s standard
deviations with a correlation closer to 1.

**Link Travel Time Reliability**

In this paper, the Bureau of Public Roads (BPR) formula is used for link performance (Chen
et al. 2002 and Lo et al. 2005):

\[
T_i(x_i, C_i) = t_i \left[ 1 + \beta \left( \frac{x_i}{C_i} \right)^\alpha \right]
\]  

(6)

Where \( t_i \) and \( T_i \) are link \( i \)’s free-flow travel time (which is a deterministic parameter) and the
travel time with flow \( x_i \) respectively; \( \beta \) and \( \alpha \) are constants; \( x_i, C_i \) and \( T_i \) are random
variables. In general, the link travel time will form a probability distribution; its mean can be
determined as:

\[
E(T_i) = t_i + \beta t_i E \left( \left( \frac{x_i}{C_i} \right)^\alpha \right)
\]  

(7)

Uncertainty of travel time reliability can arise from a variety of sources. As a result, extra
time has to be allowed for this uncertainty. Link travel time reliability is defined as the
probability \( R(T_i) \) that the expected travel time \( E(T_i) \) at degraded capacity is less than the link
free flow travel time plus an acceptable tolerance \( (\delta) \). The value \( \delta \) is related to the level of
service that should be maintained despite the capacity degradation (or it can be redefined as
the level of tolerance that the public is willing to accept for link travel time reliability). In this paper, we will assume that the expected link travel time will be considered at least 95% reliable as long as its value is less than or equal to an upper bound \( \{ E(T_i) \leq (T_i = t_i + \delta) \} \).

Travel time reliability \( R(T) \) can be expressed using the well-defined reliability engineering functions (failure rate or hazard rate function “\( \lambda(T) \)”). Mathematically, the relationship between the reliability and the failure rate (hazard) function can be written as in (Kececioglu 1991; Tobias and Trindade 1995; Hoyland and Rausand 1994; and Wolstenholme 1999):

\[
R(T_i) = e^{-\int_0^{T_i} \lambda(T_i) dT}
\]

(8)

The above equation is called the *generalized reliability function* and is valid for all travel time functions. For example, if the travel times of a link are well represented by Weibull distribution, then using Equation 8 yields a general reliability function for link “i” as:

\[
R(T_i) = e^{-\left(\frac{T_i - \gamma}{\eta}\right)^\beta}
\]

(9)

Where

(\( \beta \) → Shape parameter, \( 1 < \beta < 2.6 \)), this range causes the Weibull distribution to be positively skewed. For higher values (2.6 to 3.7) the coefficient of skewness approaches zero such that it could approximate the normal distribution. The Weibull distribution will be negatively skewed for values greater than 3.7.
(γ) → Location parameter, (γ = t_i = Free Flow Travel Time). The location parameter is the value of the variable at which the distribution starts and to the left of which f(T) = 0. As long as the minimum travel time on a link is less than or equal to free flow travel time, it is realistic to assume that the curve starts at the value where the probability that travel time is less than the free flow travel time is zero. In other words, and from a reliability point of view, a link is considered 100% reliable if its travel time is less than or equal to free flow travel time.

(η) → Scale parameter, it can be calculated as a function of the acceptable upper limit of travel time and the corresponding reliability.

Substituting the free flow travel time for γ in the above general equation, Equation 9 can be re-written as follow:

$$\left[ -\ln \left( R(T_i) \right) \right] \frac{1}{\beta} = (T_i - t_i) / \eta$$

Consequently,

$$T_i = t_i + \eta \left[ -\ln \left( R(T_i) \right) \right] \frac{1}{\beta}$$

(10)

Based on the new reliability definition in this paper, substitute for \((T_i = t_i + \delta)\) in Equation 10 when \(R(T_i)\) is at least 95%, then we get:

$$\left( t_i + \delta \right) = t_i + \eta \left[ -\ln \left( 0.95 \right) \right] \frac{1}{\beta}$$
It is known that the mean of the Weibull distribution is given as \[ \bar{y} = \gamma + \eta \Gamma\left(\left(\frac{1}{\beta}\right) + 1\right) \], where \[ \Gamma\left(\left(\frac{1}{\beta}\right) + 1\right) \] is the Gamma function. The minimum Gamma function is obtained at \( \beta = 2.17 \) (Kececioglu 1991; Tobias and Trindade 1995; Hoyland and Rausand 1994; and Wolstenholme 1999). Then, substitute for \( \beta = 2.17 \) to minimize the Weibull mean, we can get the scale parameter \( \eta \) as follows:

\[
\eta = \frac{\delta}{\left[-\ln(0.95)\right]^{1/2.17}} = \left(\frac{\delta}{0.2544}\right)
\]

Similarly, if the travel times of a link are represented by the Exponential distribution with a mean failure rate (\( \lambda \)), then the travel time reliability function for link \( i \) can be written as:

\[
R (T_i) = e^{-\int_0^{T_i} \lambda (T_i) dT} = e^{-\lambda (T_i - \gamma)} = e^{-\lambda (T_i - t_i)}
\]

The Exponential distribution scale parameter (1/\( \lambda \)) can be estimated by using the above Weibull equation with shape parameter \( \beta = 1 \) as follows:

\[
\frac{1}{\lambda} = \frac{\delta}{\left[-\ln(0.95)\right]} = \left(\frac{\delta}{0.0513}\right)
\]

These thresholds were merely assumptions that need to be verified with real-life data through comprehensive traveler behavior surveys, we did not have the appropriate resources to conduct such surveys at the time of writing this paper. Accordingly, we recommend conducting a national survey to determine the public’s level of travel satisfaction (in terms of travel time reliability). Based on the survey responses we could determine the different
levels of reliability (and tolerance thresholds) above the free flow travel time for a specific
c facility. The survey results should be used to replace the assumed travel time tolerance
threshold for 95% reliability in the paper. Indeed, the basic steps of this methodology still
apply with real life data albeit using different thresholds. This only emphasizes the
flexibility of the new method.

Network System Reliability

The transportation network is a collection of links arranged and designed to achieve desired
functions with acceptable performance and reliability. The relationship between the network
system reliability and the reliability of its links is often misunderstood. For example, the
following statement is false: “if all of the links in a system have 95% reliability at a given
time then the reliability of the system is 95% for that time.” To compute the reliability of a
system, the configuration of the links and how they are arranged (in series, in parallel, or as a
combination of both) must be first determined (Kececioglu 1991; Tobias and Trindade 1995;
Hoyland and Rausand 1994; Bell and Iida 1997; and Wolstenholme 1999).

In a series configuration, a failure of any link results in failure for the entire system. In other
words, all $M$ links in a series system must succeed for the system to succeed. The reliability
of the system is equal to the product of the reliabilities of its links. Therefore, the link with
the smallest reliability has the biggest effect on the system's reliability. As a result, the
reliability of a series system is always less than the reliability of the least reliable link. In a simple parallel system, at least one of the links must succeed for the system to succeed. In other words, all $M$ links must fail for the system to fail. Observe the contrast with the series system, in which the system reliability was the product of the link reliabilities. The parallel system has the overall system unreliability as the product of the link unreliabilities.

However, many smaller systems can be accurately represented by either a simple series or parallel configuration, there may be larger systems that involve both series and parallel configurations in the overall system. Calculating the reliabilities for the individual series and parallel sections and then combining them in the appropriate manner is the proper way of analyzing such systems. This methodology is illustrated in the following example. Consider a system with three links. Links A and B are connected in series and link C is connected in parallel with the first two. Treating links A and B as one link with a reliability of $(R_{ARB})$ in parallel with link C, then the reliability of the system is calculated as:

$$R_S = 1 - \left[ (1 - R_{ARB})(1 - R_C) \right] \quad (14)$$

Another approach for estimating the reliability is to define the successful paths for this system:

$$E_1 = AB \quad and \quad E_2 = C$$
The reliability of the system is simply the probability of the union of these paths:

\[ R_S = P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2) \]

\[ R_S = P(AB) + P(C) - P(ABC) \]

\[ = R_A R_B + R_C - R_A R_B R_C \]

(15)

Generally, for the successful multi-path network system we can manipulate Equation (15) to estimate reliability as follows:

\[ R_S = 1 - \left[ \left( 1 - R_{Path I} \right) \left( 1 - R_{Path II} \right) \left( 1 - R_{Path III} \right) \ldots \left( 1 - R_{Path J} \right) \right] \]

\[ = 1 - \prod_{J=1}^{W} \left( 1 - R_{Path J} \right) \]

(16)

Where \( J \) is the path label and \( W \) is the number of possible paths in the transportation network.

**Numerical Example**

In this section, an example of a hypothetical network is illustrated in Figure 3.2. This network has five multilane uninterrupted flow highway links with 50 mph free flow speed and two traffic zones. The links are labeled 1 through 9. The link free flow travel times are in parenthesis on each link. Under normal conditions, there are three link-paths between origin (A) and destination (B). These paths will be referred to as: **Path I**: A-Link 1-Link 3-B, **Path II**: A-Link 2-Link 4-B, and **Path III**: A-Link 2-link9-Link 3-B. Sources of unreliability such as road incident, construction work zone, and environmental conditions are inevitable in the transportation system. They cause performance degradation by reducing the
network link capacities leading to various service states of the network. Each link in the network is assumed to have various states. The degraded state is the condition in which the capacity of a link is reduced by a percent (θ) from its mean value (assumed 2000 pcphpl in this example). A range of the reduction percentages (i.e. θ = 10%, 20%,..., 50%) will be tested to examine the effect of link capacity reduction on the network reliability. In this numerical example, the coefficients of variation or CV of both capacity and demand are assumed to be 5% and 10% respectively. Also, the link travel time function used is the BPR standard function with $\beta = 0.15$ and $\alpha = 4$ as mentioned in Chen et al. (2002). Weibull and Exponential travel time distributions will be compared in estimating link travel time reliability.

**Link Capacity Reliability**

For simplicity, we assume statistical independency; or the correlation coefficient between capacity and demand ($\rho = 0$). Also, we assume that the link will be at least 95% reliable as long as the demand does not exceed the capacity. This assumption is based on the HCM2000 for multilane uninterrupted flow with free flow speed 50 mph and capacity 2000 pcphpl (Roger et al. 2003), the reduced speed is 47.5 mph (95% of the free flow speed). To achieve 95% reliability at demand level 1.0 (demand level is defined as demand normalized by capacity), the relationship between the reliability index and the acceptable extra demand can be obtained as follows:
\[ \phi_i = \frac{\bar{C}_i (\varepsilon_i + 1) - \bar{C}}{\sqrt{\sigma^2(C_i) + \sigma^2(x_i)}} = \frac{\bar{C}_i (\varepsilon_i + 1) - \bar{x}_i}{\sqrt{(CV_c * \bar{C}_i)^2 + (CV_s * \bar{x}_i)^2}} \]

Where, CV is the coefficient of variation. Since demand = capacity at demand level 1.0 and we have 95% reliability then:

\[ \phi_i = \frac{\bar{C}_i (\varepsilon_i + 1) - \bar{C}}{\sqrt{(CV_c * \bar{C}_i)^2 + (CV_s * \bar{x}_i)^2}} = \frac{\bar{C}_i \varepsilon_i}{\bar{C}_i \sqrt{(CV_c)^2 + (CV_s)^2}} \]

\[ \phi_i = \frac{\varepsilon_i}{\sqrt{(CV_c)^2 + (CV_s)^2}} \quad (17) \]

The reliability index can be obtained through the standard normal distribution table as:

\[ (R_i = \psi(\phi_i) = 0.95) \Rightarrow \phi_i = 1.65 \]

Using Equation 17, and substituting the assumed values of CVs for both capacity and demand in this example (5% and 10% respectively), the tolerance for demand exceeding capacity is \( (\varepsilon_i = 18.45\%) \). Accordingly, the failure probability (Equation 4) can be rewritten as:

\[ p(f) = [P(x_i - C_i \geq 0.1845\bar{C}_i) \quad \text{or} \quad P(S_i \geq 0.1845\bar{C}_i)] = 1 - \psi(\phi_i) \]

The link capacity reliability is calculated as \( (R_i = \psi(\phi_i)) \) using the standard normal distribution table, where \( \phi_i \) is calculated as in Equation 5.

Figure 3.3 shows how the capacity reliability is affected by the changes in the travel demand level. The capacity reliability is 100% for demand level = 0.9. For demand levels exceeding 0.9 the capacity reliability starts to deteriorate. For example, if the demand level increases
from 1.0 to 1.2, the corresponding capacity reliability value drops significantly from 95% to 45% respectively (Independent curve).

Also, Figure 3.4 examines the effect of statistical dependency on capacity reliability. By releasing the assumption of statistical independency, and assuming that the correlation among all link capacities and travel demands is \( \rho = 0.5 \), the results clearly indicate that dependency has an impact on the capacity reliability measure. Figure 3.4 illustrates that the curve is pushed up in case of correlation as compared to no correlation as long as the demand level is less than \((1+\epsilon)\) or 1.18. For example, at demand level 1.05, the link capacity reliability increases from 88% (no correlation) to 92% (correlation = 0.5). As a result, it is recommended to estimate the actual correlation coefficient between demand and capacity, because this will increase the accuracy in estimating the capacity reliability and it will enhance the information provided to the road users. A future paper will elaborate on the effect of link dependency on reliability estimation.

Note that the trend of dependency in Figure 3.4 is reversed when demand level exceeds \((1+\epsilon)\). The reverse in trend after the cut off point is related to the assumed normal distributions for both demand and capacity. Because of normality assumptions, we are expecting two types of errors: Type I and Type II, represented by dashed areas in Figures 3.4 and 3.5. Type I Error or the probability of failure \((1-R(T))\): rejecting a true null hypothesis applies if the probability or the capacity reliability is greater than 50%. The null hypothesis
is defined as follows: the difference between demand and \((1+\varepsilon)\) times the capacity is statistically insignificant. Type II Error with probability \(R(T)\): failing to reject a false null hypothesis occurs if the probability or the capacity reliability is less than 50\%. To illustrate this, consider demand level=1.05. The Type I error is 12\% (no correlation) and 8\% (correlation = 0.5). Furthermore, at 1.3 demand level, Type II error is 20\% for no correlation and 15\% for correlation = 0.5.

The effects of travel demand variation on the expected capacity reliability measure is examined by applying a range of travel demand coefficients of variation (i.e. CV = 10\%, 30\%, and 50\%). Figure 3.4 demonstrates that the higher the variation in travel demand the lower the expected capacity reliability. For example, at 0.9 demand level, capacity reliability decreases from 99.7\% to 85\% and then down to 73.5\% as the travel demand coefficients of variation increase from 10\% to 30\% and then to 50\% respectively. Also, when the demand level is less than 1.18 or \((1+\varepsilon)\), which is the cut off point, an increase in demand CV causes the reliability curves to be pushed down increasing Type I error. As mentioned earlier, as the demand level exceeds \((1+\varepsilon)\), the trend of the reliability curves turns around but this also means that the more variation in the travel demand the more Type II error we get and the less accurate will be the capacity reliability estimates.
Link Travel Time Reliability

As noted earlier, the expected travel time is affected by both travel demand and capacity (Equation 7). The Weibull with shape parameter ($\beta = 2.17$) and link capacity reduction percentages ($\theta = 10\%, 20\%, \ldots, 50\%$) are tested. Figure 3.5 depicts the travel time reliability and unreliability curves using the Weibull travel time distribution (Equation 9). It shows the effect of travel demand level on the expected link travel time reliability. For demand levels less than 0.8 the travel time reliability is about 100% and seems to be independent of demand and capacity variations. Travel time reliability continues to drop slightly for demand levels higher than 0.8 but lower than 1.0 where it reaches 95%. This is similar to the case of the capacity reliability measure. As the demand level increases above this level, the expected link travel time reliability declines quickly.

Figure 3.6 and Figure 3.7 show the travel time reliability and unreliability curves for two travel time distributions: Exponential (Equation 12) and Weibull (Equation 9). Both figures illustrate the relationship between the link travel time reliability and the percentage of travel time above the free flow travel time. As expected, the reliability decreases as the travel time increases. Therefore, a lower value of the travel time implies that the link is operating at a higher level of service. Obviously, the performance of the Weibull with shape parameter ($\beta = 2.17$) and scale parameter ($\eta$, as in Equation 11) is much better than the Exponential distribution with failure rate ($\lambda$, as in Equation 13).
Figure 3.6 illustrates the slow convergence of the Exponential distribution. Specifically, the travel time reliability of the link is approximately 71% with 100% travel time above the free flow travel time. Clearly, this will give a false impression about reliability because regardless of the increase in link travel time the link remains reliable. As such, the Weibull distribution is recommended over the Exponential distribution for the analysis of the network travel time reliability. However, analysis of real life travel time data sets is a must before a final decision can be made on the most appropriate distribution for computing the travel time reliability performance measure.

**Network System Reliability**

In constructing network system reliability, a common practice is to assume independent link capacity degradation. The independence assumption is mathematically convenient but may be not be valid in real world transportation networks, this is the subject of a future paper, however. Also, enumeration of all possible network states is impractical because the number of network states grows exponentially. For example, there are $M^N$ states for the network in our example (Figure 3.2), where $M$ is the number of links and $N$ is the number of possible states for each link. For simplification, only the worst probable states of the network are analyzed which means that each link capacity will be degraded by the same percentage ($\theta = 10\%, 20\%, \ldots, 50\%)$ at the same time. Hence, we will have five states in addition to the base state (no capacity degradation or ($\theta = 0$)).
Figure 3.6 shows the travel time reliability as a function of the percentage of the travel time above the free flow travel time for various link capacity states. In this paper, we assume that travel time is acceptable up to the point when demand reaches capacity. This means that the acceptable extra time above the free flow travel time will occur at the capacity level (demand = capacity). Hence, the acceptable travel time threshold ($\delta$) will be 15% of the free flow travel time. This is because $\beta$ in the BPR function = 0.15. Hence, the upper travel time threshold will be the free flow travel time plus the acceptable time or 115% of the free flow travel time.

The Weibull distribution scale parameter can be calculated using Equation 11:

$$\eta = \left( \frac{\delta}{0.2544} \right) = \left( \frac{0.15t_i}{0.2544} \right) = 0.5896 \times t_i$$

Table 3.1 and Table 3.2 present results of the system network travel time reliability (with the desired link reliability being at least 95% at demand level 1.0) and the system capacity reliability respectively. These two tables depict both the travel time and capacity reliabilities of each link, path and the overall network for ($\theta = 10\%, 20\%, \ldots, 50\%$). For example, to calculate the travel time reliability of Link 2 with $t_i = 8$ minutes at capacity reduction percentage ($\theta = 30\%$), the travel time is 9.58 minutes, which is greater than the upper threshold (9.2 min.). The calculated reliability is expected to be less than 95% because the percentage of travel time above the free flow travel time is higher than $\delta$ (15%). The link travel time reliability is calculated as follows:
In Table 3.2, the link capacity reliability is calculated directly using the basic Equation 5 and
the link independency assumption \((\rho = 0)\): 

\[
\phi_i = \frac{\varepsilon C_i - [\bar{x}_i - \bar{C}_i]}{\sqrt{\sigma^2 C_i + \sigma^2 x_i - 2\rho \sigma C_i \sigma x_i}} = \frac{(1.1845 \times 1400 - 1500)}{\sqrt{(0.05 \times 1400)^2 + (0.10 \times 1500)^2}} = 0.96
\]

Then, link capacity reliability can be obtained from the standard normal distribution as:

\[
(R_i = \psi(0.96) = 83.05\%)
\]

The shaded cells in the two tables are for cases of demand exceeding degraded capacity. The
path travel time and capacity reliabilities are calculated based on the reliability formula for
the series configuration (Equation 16) for \(R_s\). For example, to calculate the travel time or
capacity reliability of \textbf{Path I}: A-Link 1-Link 3-B, we multiply the reliabilities of \textbf{Link 1} and
\textbf{Link 3} as follows:

\[
R_{Path} = \prod_{i=1}^{M=3} (R_i) = (R_{Link 1} \times R_{Link 3})
\]

There are three paths in this network: \(Path_1 = \{l_1, l_3\}\), \(Path_2 = \{l_2, l_4\}\) and
\(Path_3 = \{l_2, l_3, l_3\}\). The three paths are connected in parallel, so the system reliability is
calculated using Equation 18:

\[
R_s = 1 - \left[ (1 - R_{Path_1})(1 - R_{Path_2})(1 - R_{Path_3}) \right]
\]

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Table 3.1 indicates that system travel time reliability results are similar to those of capacity reliability in Table 3.2 especially when demand is less than the capacity. Note that, in this numerical example, a small reduction in link capacity would cause only a small or no variation in both travel time reliability and capacity reliability given that the remaining capacity is higher than the traffic flow. In cases of highly reliable networks in which both capacity reliability and travel time reliability of each link is higher than 95%, the two measures show insignificant differences because the capacity degradation caused insignificant travel time variability. And, the travelers could depart their origins and reach their destinations on time without the need to account for additional travel time or leave early. However, there are large differences between the two measures (travel time and capacity reliabilities) for cases with large capacity degradations (e.g., 40% and 50%) that cause demand to exceed capacity.

The results in this numerical example change significantly when the network becomes unreliable. Travelers need to account for an additional travel time to ensure on time arrival to destinations. This information could be disseminated to roadway users before making a trip to help them decide on their departure time. Also, the travel time reliability could be disseminated while en-route through cell phones, radio, or changeable message signs to reduce travelers’ anxiety about the unknown and to provide them with possible diversion alternatives.
In summary, both travel time reliability and capacity reliability are consistent measures for reliability of the road network, but each may have a different use. Specifically, capacity reliability measure is of special interest to transportation network planners and engineers because it addresses the issue of whether the available network capacity relative to the present or forecasted demand is sufficient, whereas travel time reliability is especially interesting for network users.

**Conclusions**

Network reliability is a subject of great practical importance to planners and engineers involved in network design. Transportation system could rely on current and projected trends in the travel time reliability to assess transportation deficiencies and potential improvements, to set funding or programming priorities by comparing between competing alternatives, and to provide up-to-date reliable travel time information to the commuting public based on current or historical databases.

This paper developed a new method for estimating reliability and applied it to a hypothetical network to estimate network travel time and capacity reliability measures under non-recurring congestion conditions with degraded link capacities. Both measures demonstrated similar performance and have the potential of being useful for estimating the reliability of a road network. However, travel time reliability is more interesting and easier to understand
by the public. This paper demonstrated that the Weibull distribution should be used instead of the Exponential distribution in reliability analysis.

In this paper, we defined reliability in a way that is totally different from the existing methods. Unlike the existing methods (Florida and Buffer Time) which define reliability in terms of travel time variability, the definition of reliability in the new method puts more emphasis on the user’s perspective. A roadway segment is considered at least 95% reliable if its travel time is less than or equal to the travel time when demand does not exceed capacity. The new method is more sensitive to the users’ perspective since it reflects that an increase in the segment’s travel time should always result in less travel time reliability as shown in Figure 3.7. By doing this we assume that the public will be satisfied if traffic conditions allow them to travel the roadway facility at 95% of the free flow speeds. While this new method did not ignore the user, it really sets a level of travel quality expectation by the road customer (or the traveler). Thresholds assumed in this paper still need to be verified with real life data through comprehensive traveler behavior surveys. As such, we strongly recommend conducting a national survey to determine the public’s level of travel satisfaction (in terms of travel time reliability). Also, more accurate assessment of reliability levels matched with travel time thresholds could be determined based on such surveys. As soon as the survey results are known, thresholds assumed in this paper can be replaced with more realistic ones. The basic steps of this methodology still apply with real life data albeit using different thresholds. This emphasizes the flexibility of the new method.
Only a small size network was tested in this paper but the method has true potential and can be extended to large scale networks. Future research will focus on using actual field data to develop the best fit distributions for both capacity and travel time reliabilities, conduct a survey to find the real life thresholds for reliability, and expand the size of the network by dealing with real life transportation networks. Additionally, the impact of quantifying travel time reliability on user equilibrium under various travel choices will be tested in the future. The new method will be extended further to demonstrate the complicated effects of link failure dependency, and finally to accommodate variations in the O-D demand table.

**References**


Hoogendoorn, S., and Van, Z., (2000). “Robust and Adaptive Travel Time Prediction with Neural Networks.” TRAIL Research School,


Table 3.1: Network system travel time reliability at different degraded capacity states

<table>
<thead>
<tr>
<th>Description</th>
<th>Link states (N = 6) based on capacity reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \theta = 0.00 )</td>
</tr>
<tr>
<td>Links (M=5)</td>
<td></td>
</tr>
<tr>
<td>(Equation 9)</td>
<td></td>
</tr>
<tr>
<td>Link1 (x = 1000)</td>
<td>99.99%</td>
</tr>
<tr>
<td>Link2 (x = 1500)</td>
<td>99.58%</td>
</tr>
<tr>
<td>Link3 (x = 1300)</td>
<td>99.88%</td>
</tr>
<tr>
<td>Link4 (x = 1200)</td>
<td>99.94%</td>
</tr>
<tr>
<td>Link9 (x = 300)</td>
<td>100.00%</td>
</tr>
<tr>
<td>Paths</td>
<td></td>
</tr>
<tr>
<td>Path I: (A, Link1, Link3, B)</td>
<td>99.87%</td>
</tr>
<tr>
<td>Path II: (A, Link2, Link4, B)</td>
<td>99.52%</td>
</tr>
<tr>
<td>Path III: (A, Link2, Link9, Link3, B)</td>
<td>99.46%</td>
</tr>
<tr>
<td>System (Equation 16)</td>
<td>Path I, Path II &amp; Path III</td>
</tr>
</tbody>
</table>
Table 3.2: Network system capacity reliability at different degraded capacity states

<table>
<thead>
<tr>
<th>Description</th>
<th>Link states (N = 6) based on capacity reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\theta = 0.00$</td>
</tr>
<tr>
<td>Links (M=5) (Figure 3.3)</td>
<td></td>
</tr>
<tr>
<td>Link1 (x = 1000)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Link2 (x = 1500)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Link3 (x = 1300)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Link4 (x = 1200)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Link9 (x =300)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Paths</td>
<td></td>
</tr>
<tr>
<td>Path I: (A, Link1, Link3, B)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Path II: (A, Link2, Link4, B)</td>
<td>100.0%</td>
</tr>
<tr>
<td>Path III: (A, Link2, Link9, Link3, B)</td>
<td>100.0%</td>
</tr>
<tr>
<td>System (Equation 16)</td>
<td>Path I, Path II &amp; Path III</td>
</tr>
</tbody>
</table>
Figure 3.1: Capacity-Demand distribution (Source: Patrick et al., 2002 and Harr, 1987)
Figure 3.2: Hypothetical test network
Figure 3.3: Capacity reliability for various levels of demand
Figure 3.4: Effects of demand variation on capacity reliability
Figure 3.5: Relationship between demand level and travel time reliability with Weibull/Exponential link travel time distribution
Figure 3.6: Travel time reliability with Exponential link travel time distribution
Figure 3.7: Travel time reliability with Weibull link travel time distribution
CHAPTER 4
UTILIZING A REAL LIFE DUAL LOOP DETECTOR DATA TO DEVELOP A NEW METHODOLOGY FOR ESTIMATING FREEWAY TRAVEL TIME RELIABILITY

Abstract

Travel time reliability is an important system performance measure for freeway traffic operations. It captures the variability experienced by individual travelers and it is an indicator of the operational consistency of a facility over an extended period of time. A real life transportation data was utilized to develop a new methodology for estimating travel time reliability of the I-4 corridor in Orlando, Florida. Four different travel time distributions: Weibull, Exponential, Lognormal, and Normal were tested. The developed best-fit statistical distribution (Lognormal) can be used to compute and predict travel time reliability of freeway corridors and report this information in real time to the public through traffic management centers. When compared to existing Florida and Buffer Time methods, the new reliability method showed higher sensitivity to geographical locations, which reflects the level of congestion and bottlenecks. Another advantage of the new method is its ability to estimate the travel time reliability as a function of departure time.
**Key Words:** Reliability, Freeway Corridors, Travel Time Distribution.

**Introduction**

During the 20th century, transportation programs were focused on the development of the basic infrastructure for the transportation networks. In the 21st century, the focus has shifted to management and operations of these networks (NCHRP, 2003). Reliability measures are critical in judging the performance of the transportation system and in evaluating the impact of new Intelligent Transportation Systems (ITS) deployment.

Reliability engineering is a well-established area. Its theory has been widely associated with the design and management of communication and computer networks and the performance of mechanical equipment. In this context, reliability is defined as “the probability that an entity will perform its intended function(s) satisfactory or without failure for a specified length of time under the stated operating conditions at a given level of confidence” (Kececioglu, 1991).

In the transportation field, the capacity of a freeway link can degrade due to various factors, such as incidents, work zones, weather conditions, and natural/man-made disasters. Also, the demand fluctuates, sometimes due to special events, or within the day and/or between days. These variations lead to unreliable travel times. Also, the HCM’s six levels of service (LOS)
do not capture the variability in travel time and are used primarily in designing and analyzing short, homogeneous sections of freeways (Chen et al., 2003).

*Travel time reliability* is concerned with the probability that a trip between a given Origin-Destination pair can be successfully made within a specified time interval (Chen and Recker, 2000). This measure is used to evaluate network performance under normal traffic conditions subject to daily flow variations. Different researchers have used different definitions of transportation network travel time reliability. For example, Shaw and Jackson (2003) defined reliability as the variability between the expected travel time (based on scheduled or average travel time) and the actual travel time (due to the effects of non-recurrent congestion or fluctuation in demand during recurrent congestion).

Apart from the effect on normal day-to-day life, transportation systems are an important lifeline in the event of a natural or man-made disaster, e.g. floods, earthquake, hurricanes, and bomb explosions (Du and Nicholson, 1997). Freeway corridors, which are an essential part of the transportation network, provide access to emergency services, aid workers and relief supplies. In addition, other lifelines (electricity, water supply, and communication networks) can be restored quickly if transportation access to damaged sites is fast and reliable.
Travel Time Reliability Measures

The following provides a quick overview of the travel time reliability measures used in the US.

Percent Variation

Statistically, this is known as the “Coefficient of Variation or CV”. It is calculated as the standard deviation divided by the mean. The CV provides a clearer picture of the trends and performance characteristics than the standard deviation. A traveler could multiply his or her average travel time by the percent variation, and then add that product to his or her average trip time to get the time needed to be on-time about 85% of the time (Turner et al., 1996).

California Reliability Method

California Transportation Plan (1998) defines reliability as the variability between the expected travel time and the actual travel time (Lomax et al., 2004). The Standard Deviation of Average Trip Time Distribution is used as the reliability index. Segments with insignificant travel time variations from day-to-day “have narrower curves of average trip times” and are considered reliable. Since this measure reflects the variation in travel times more than the acceptability of the travel times to the user, it is incomplete.
**Florida Reliability Method**

The Florida Reliability Method was derived from the FDOT’s definition of reliability of a highway system as the percent of travel on a corridor that takes no longer than the expected travel time plus a certain acceptable additional time (FDOT, 2000). The percent of reliable travel is calculated as the probability of travel that is acceptable (takes no longer than this acceptable travel time). Mathematically, reliability \( R(t) \) is defined as:

\[
R(t) = P(x < X + \Delta) = P(x < TT)
\]

Where:

\( X \rightarrow \) The median travel time across the corridor during the period of interest; and

\( \Delta \rightarrow \) A percentage of the median travel time during the period of interest, percentages of 5%, 10%, 15%, and 20% above the expected travel time are currently being considered but a decision has not been finalized (Shaw and Jackson, 2003).

**Buffer Time**

The buffer time concept may relate particularly well to the way travelers make decisions, it uses minutes of extra travel time needed to allow the traveler to arrive on time (Chen et al., 2003). The buffer time would be the difference between the average and the upper limit of the 95% confidence interval as calculated from the annual average. The main problem is that the public does not readily understand the Buffer Time.
By tracking these reliability measures, the Buffer Time and Florida Reliability Model rose above others as the preferred measures, and it seemed to resonate with most audiences. However for these measures, it is not certain what level of reliability (e.g., 85%, 90%, or 95%) should be used. Previous studies assumed Weibull and Normal distributions for travel time reliability but this assumption was never verified with real-life travel time data. This has a direct impact on the accuracy of predicting reliability.

As such, the main goal of this paper is to develop a methodology that will address this major shortcoming. Specific objectives of this research include the development of an efficient methodology for predicting travel time reliability as a new performance measure on freeway corridors based on real-time and historical loop detector data. The travel time reliability model will be implemented on a section of Interstate 400 (I-4), a major transportation corridor in Orlando, Florida. This section carries large volumes of long-distance, inter-regional and intrastate commercial traffic and commuters.

This paper has three more sections in addition to the first one. Section 2 illustrates the traffic database that will be used in this research. Section 3 clarifies the steps that will be conducted to develop the proposed travel time reliability model. Section 4 shows the results of applying the new methodology to the I-4 corridor and a comparison between the new method with the FDOT and Buffer Time methods.
**Traffic Data**

The Orlando Regional Transportation Management Center (RTMC) monitors approximately 50 miles of I-4. The study section covers 35.0 miles of I-4 (eastbound direction) with 29 on-ramps and 31 off-ramps. Dual loop detectors are placed at approximately 0.5 miles apart in each lane to collect volume, lane occupancy, and speed data. The data from these detectors are sent automatically to the RTMC every 30 seconds in a binary format and eventually converted to an ASCII-text format. The University of Central Florida (UCF) has used the loop detectors data to update the interactive GIS speed map that UCF developed on the World Wide Web site (www.iflorida.org). In addition, UCF developed detailed quality control and imputation procedures that were published in TRB (Al-Deek and Chandra, 2004). Travel time between any on and off ramp on I-4 was calculated using the real time “filtered” loop speed data and stored in the I-4 data warehouse during 2003 (Al-Deek et al., 2004).

**Modeling Methodology**

A software program was built to query specific data. The program was applied to obtain four consecutive weeks of data (20 weekdays and 6 weekend days) from October 6th to October 31st, 2003. The program was written in Visual Basic (VB) and was run on Microsoft Visual Studio. The mean travel time was calculated for time departure intervals of 5 minutes during the weekday evening peak period in the eastbound direction, which started at 3:30 PM and
ended at 6:30 PM. The preliminary analysis indicated that weekends had a different peak period, so this study will focus on weekdays. In this study, the origins and destinations were defined to begin and end at major interchanges (from on-ramp to off-ramp end points) where traffic conditions were likely to change. The set of origins and destinations were labeled to the closest loop detector ID. For example, the closest loop detector to US 192 on-ramp was station ID5. This defined an origin, while the set of destinations (off-ramps) were labeled to the closest loop detector station ID (i.e., 14, 22,..., 69) as shown in Figure 4.1.

Four statistical distributions (Weibull, Exponential, Lognormal, and Normal) for travel time data were tested to find out which one had the best fit with real data. The I-4 section under study started from E.US 192 (Station 5) to Lake Mary Boulevard (Station 69) and was divided into seven segments, see Figure 4.1. The freeway segments were approximately five miles in length. The beginning and ending of each segment to the closest start and end loop detector station IDs and segment lengths are demonstrated in Tables 4.1 and 4.2, which will be explained later. Furthermore, the number of weekdays with data included nine different levels as follows: Five levels representing the weekday (Monday-Friday), and four levels representing the number of consecutive weekdays under consideration in the analysis sample (5, 10, 15 and 20 days). The five levels are explained as follows: The first level (M) included data from Mondays of the four weeks analyzed in October 2003; the second level (T) included data from Tuesdays of the four weeks analyzed in October 2003, and so on. The four levels (5, 10, 15, and 20 days) explored the effect of expanding the sample by using data
from different weekdays within the same week or different weekdays from different weeks. For example, the first level (5 days) included data from the first week of October 2003 (Monday through Friday). The second level (10 days) included data from the first two consecutive weeks in October (October 6th to October 19th, 2003), and so on. Accordingly, the maximum number of weekdays that were used in this analysis is 20 days (4 consecutive weeks in October 2003). The possible combination scenarios of the above variables and levels resulted in \((4 \times 9 = 36)\) different scenarios per freeway segment.

To check the validity of our assumptions regarding the specific travel time distribution (Normal, Exponential, Weibull, or Lognormal), we use the Goodness of Fit (GoF) tests which are based on either the cumulative distribution function (CDF) such as Anderson-Darling (AD) and the Kolmogorov-Smirnov (KS) tests or the probability density function (pdf) such as the Chi-Square test. We have selected AD because it is among the best distance tests for small and large samples, and various statistical packages are widely available for this AD test (Shimokawa and Liao, 1999). Anderson-Darling statistic is a measure of how far the plotted points fall from the fitted line in a probability plot. The statistic is a weighted squared distance from the plotted points to the fitted line with larger weights in the tails of the distribution with the null hypothesis:

\[
H_0: \text{The data followed the specified distribution.}
\]

\[
H_a: \text{The data did not follow the specified distribution.}
\]
Also, the 90th percentile of the absolute errors, which were calculated by comparing the predicted and the actual distribution, is used as another evaluation criterion to assess the assumed distribution parameters.

**Link Travel Time Reliability Models**

Travel time reliability $R(T)$ can be expressed using the well-defined reliability engineering functions (failure rate function “$\lambda(T)$”). Mathematically, the relationship between the reliability and the failure rate (hazard) function can be written as (Kececioglu, 1991; and Birolini, 1999):

$$R(T) = e^{-\int_0^T \lambda(T) dT}$$

Where: $\lambda(T) = \left(\frac{f(T)}{R(T)}\right)$ and $f(t)$ is the probability distribution function

The above equation is called the *generalized reliability function* and is valid for all travel time functions. Once the travel time distribution of a link is known, then the reliability function of that link can be determined. The SAS software program is used to calculate the distribution parameters and the evaluation criteria. The following subsections briefly demonstrate the distributions’ parameters and the corresponding reliability functions.
**Weibull Distribution**

The Weibull distribution is a general-purpose reliability distribution. Because of its flexible shape and ability to model a wide range of failure rates. In its most general case, the three-parameter Weibull pdf is defined by:

\[
f(T) = \frac{\beta}{\eta} \left( \frac{T - \gamma}{\eta} \right)^{\beta-1} e^{-\left( \frac{T - \gamma}{\eta} \right)^\beta}
\]

Where

- \( f(T) \geq 0, \ T \geq \gamma, \ \beta > 0, \ \eta > 0, \ -\infty < \gamma < \infty, \)
- \( (\beta) \rightarrow \text{Shape parameter}, \)
- \( (\eta) \rightarrow \text{Scale parameter}, \)
- \( (\gamma) \rightarrow \text{Location parameter}, \)

The Weibull reliability function \( R(T) \) using the general equation is:

\[
R(T) = e^{-\left( \frac{T - \gamma}{\eta} \right)^\beta} = 1 - F(T)
\]

**Exponential Distribution**

The Exponential distribution is a special case of the Weibull distribution with shape parameter \( \beta = 1. \) As a result, if the travel times of a link are well represented by the
exponential distribution with a scale parameter \((1/\lambda)\) and a mean failure rate \((\lambda)\), then using Equation 3, the travel time reliability function can be written as:

\[
R(T) = e^{-\lambda(T-\gamma)}
\]  

(4)

Lognormal Distribution

The Lognormal distribution has a very flexible probability density and failure rate functions. It has a variety of shapes that can resemble the shapes of the Weibull distribution. This flexibility makes the lognormal an empirically useful model for right skewed data (i.e. travel time). The three-parameter lognormal distribution \((\gamma, T_0, \sigma_T)\) pdf is given by,

\[
f(T) = \frac{1}{(T-\gamma)\sigma_T\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln(T-\gamma)-\bar{T}}{\sigma_T}\right)^2}
\]  

(5)

Where

- \(f(T) \geq 0, T \geq \gamma, -\infty < T' < \infty, \sigma_T > 0, -\infty < \gamma < \infty\),
- \(T' = \ln(T) \rightarrow \) Where "T" is the travel time,
- \(\gamma \rightarrow \) Location parameter,
- Scale parameter \(\rightarrow \bar{T} = \frac{1}{N} \sum_{i=1}^{N} \ln(T_i) = \frac{1}{N} \sum_{i=1}^{N} (T_i)\),
- Shape parameter \(\rightarrow \sigma_T = \frac{\sqrt{\sum_{i=1}^{N} (T_i^2) - N(T)^2}}{\sqrt{N-1}}\),
• Median \( T_{50} = e^{\bar{T}} \) or \( \bar{\gamma} = Ln(T_{50}) \)

Then, the reliability function can be written as:

\[
R(T) = 1 - F(T) = 1 - \Phi \left( \frac{Ln(T - \gamma) - Ln(T_{50})}{\sigma} \right)
\]  \hspace{1cm} (6)

**Normal Distribution**

The normal distribution is the logarithm of the lognormal distribution with location parameter \( \gamma = 0 \), mean or scale parameter \( \mu = Ln(T_{50}) \) and standard deviation or shape parameter \( \sigma = \sigma_{\gamma} \). The reliability function can be written as:

\[
R(T) = 1 - F(T) = 1 - \Phi \left( \frac{T - \hat{\mu}}{\hat{\sigma}} \right)
\]  \hspace{1cm} (7)

**System Travel Time Reliability**

The freeway corridor is a collection of links arranged and designed to achieve desired functions with acceptable performance and reliability. The relationship between the freeway corridor system reliability and the reliability of its links is often misunderstood. For example, the following statement is false: “if all of the links in a system have 95% reliability at a given time then the reliability of the system is 95% for that time.” To compute the reliability of a system, the configuration of the links and how they are arranged (in series, in
parallel, or as a combination of both) must be first determined. In a series configuration, as in
the freeway corridor, a failure of any link results in failure for the entire system.

Probabilistically, the reliability of the system is then given by:

\[ R_S = P(X_1 \cap X_2 \cap X_3 \cap \ldots \cap X_n) \]
\[ = P(X_1)P(X_2 | X_1)P(X_3 | X_1 \cap X_2) \ldots P(X_M | X_1 \cap X_2 \ldots X_{n-1}) \]

Where:

- \( R_S \) = Reliability of the system
- \( X_i \) = Event of link \( i \) being operational.
- \( P(X_i) \) = Probability that link \( i \) is operational.

However, in the case of independent components, the above equation becomes:

\[ R_S = P(X_1)P(X_2) \ldots P(X_n) = \prod_{i} P(X_i) = \prod_{i} R(X_i) = \prod_{i} R_i \]  

(8)

For example, if all the components have the same reliability (\( R(x) = 0.95 \)), then the system
reliability of a series configuration of (n = 10) components will be:

\[ R_S = \prod_{i} R_i = 0.95^{10} \approx 0.60 \]

Hence, the system reliability of a series configuration is much lower than 0.95.
This section presents the application of the methodology to the I-4 corridor and data warehouse previously mentioned in page 4. Using this empirical data we come up with estimates of the travel time distributions parameters. Once the distribution with the “best” fit of the segment is selected, then an adjustment will be needed. This adjustment must reflect that 100% travel time reliability does not start right at zero travel time. It is unrealistic that any highway segment can be traversed in zero seconds no matter how fast the cars are. Also, the public has a perception of acceptable travel time threshold at which 100% travel time reliability is achieved. The logical assumption is to consider the road segment to be 100% reliable if its travel time is less than or equal to an upper threshold. We choose this upper threshold for each segment to be equal to the segment length divided by the speed limit. By doing this we assume that the public will be completely satisfied if traffic conditions allow them to travel the roadway facility at the speed limit.

**Segment Travel Time Distribution**

The SAS software was used to fit the data to the theoretical travel time distributions (Weibull, Exponential, Lognormal, or Normal). The results are presented below in tables along with the accompanying graphs of the best fit.
Data was grouped in samples in different ways while fixing the same distribution each time. First, the distribution parameters were estimated using data for the same day of the week (e.g., Mondays only). Then, the parameters were estimated with extended samples that included days of two consecutive weeks, days of three consecutive weeks, and finally days of four consecutive weeks.

Table 4.1 provides all four distributions and their corresponding AD statistic. Figure 4.2 shows the percentages of the fitted models that have AD values less than 1.5, which are highlighted in Table 4.1. It is obvious that, for most of the cases, and as long as data was gathered from different days of different weeks, the estimation of parameters got worse as evident in the large AD statistic. This has a negative impact on estimation accuracy. The null hypothesis is rejected at 99.9% confidence level for all AD exceeding the appropriate critical value (1.5) as in (D'Agostino and Stephens, 1986). In Figure 4.2, we found that 71.4% or more of the Lognormal models had AD values less than the critical value (1.5) for the weekdays data (i.e., Mondays, Tuesdays, …, and Fridays) and this value dropped to 42.9% for samples with mixed weekdays (e.g., 15 days).

The analysis of the 63 scenarios [9days categories × 7segments] for each distribution demonstrated that using data from the same weekdays (e.g., Mondays) yielded better results compared to mixing data from different weekdays within the same week or from different weeks in the same sample. Furthermore, the Lognormal rose above the other distributions
and proved to be the best travel time fit distribution. As a result, the rest of the paper analysis will only focus on the first five levels of data that represent weekdays (Mondays, Tuesdays, …, and Fridays). This leads to 35 scenarios [5weekdays × 7segments].

The second criterion was the estimated error percentages, which were calculated by comparing the predicted and the actual distribution. Among the analyzed 35 scenarios, the 90th percentile of the absolute errors of the Lognormal models were less than 11.66% compared to 13.12%, 23.32%, and 23.41% of the Weibull, Normal, and Exponential distributions respectively, see Figure 4.2. For illustration, for the Lognormal models (Tuesdays), it was found that 90 percent of the computed absolute errors were less than 11.66%. Consequently, Figure 4.2 proved again that the Lognormal distribution rose above the other distributions in accuracy, this was followed by the Weibull distribution. The Exponential distribution had the highest 90th percentile and the highest AD values, so it was ranked lowest.

The best distribution (Lognormal) was used to examine the similarities among the weekdays (i.e. Mondays, Tuesdays, …, and Fridays) for the same segment. The t-statistical test was used to see if there was a statistically significant difference between the weekdays and hence requiring different parameter estimates (models) for each weekday data group (i.e., Mondays, Tuesdays, …, and Fridays). Using the t-student test (two samples with unequal variances) after taking the logarithm of the travel time, because the logarithm of a Lognormal is
Normal, it was found that there was no significant difference (i.e., $P > 0.05$) between the weekdays (Mondays through Fridays) for the first segment (5-14) and the same was found for the last segment (60-69) as shown in Figure 4.3. These two segments experienced little congestion throughout the evening peak period. On the other hand, it was found that there was a significant difference (i.e., $P < 0.05$) between the weekdays (Mondays through Fridays) in the rest of the segments (e.g., segment 30-42), see right side of Figure 4.3. Consequently, it was imperative to compute the appropriate estimates of the Lognormal model parameters based on the day of the week for each of the congested segments.

**Segment Travel Time Reliability**

An adjustment was needed to estimate the travel time reliability and to achieve the following definition “a roadway segment is considered 100% reliable if its travel time is less than or equal the travel time at the posted speed limit.” The threshold or the location parameter $\gamma$ in Equation 6 had to be adjusted to reflect the acceptable travel time level (travel time at posted speed limit). The adjusted location parameter can be calculated as a function of the acceptable upper limit of travel time and the corresponding reliability. Equation 6 can be re-written as follows:

$$\sigma \Phi^{-1}(1 - R(T)) = \ln(t - \gamma) - \ln(T_{50}) \quad \Rightarrow \quad \ln(t - \gamma) = \ln(T_{50}) + \sigma \Phi^{-1}(1 - R(T))$$
Substitute for \( t = \text{distance divided by speed limit} \) and consider that \( R(T) = 100\% \), we get:

\[
\ln(t - \gamma) = \ln(T_{50}) - 3\sigma \quad \Rightarrow \quad \gamma = t - e^{\left[\ln(T_{50}) - 3\sigma\right]}
\]

The reason for substituting \( \Phi^{-1}\left[\frac{1}{2} - R(T)\right] \approx -3 \) is that under a normal curve, approximately 99\% of test observations fall within three standard deviations. Similarly, the adjusted location parameter \( \gamma \) can be calculated for the other three distributions (Weibull, Exponential, and Normal).

Figure 4.4 demonstrates the adjusted Lognormal travel time reliability models for different data levels (weekdays) and segments. Obviously, the travel time reliability model is sensitive to the geographical location that reflects the level of congestion. Figure 4.4 shows the model at Segment (5-14) where the travel speeds were almost equal to the speed limit (no congestion). Note that reliability did not vary much among weekdays for this segment. Conversely, observe the large variations in travel time reliability in the congested segments (e.g., segment 30–42 in downtown Orlando). The travel times had different patterns among the weekdays. This emphasizes the need to develop a reliability model for each day of the week (e.g., Mondays). Further, this underscores the fact that the developed models are appropriate for evaluating performance of freeway operations. They can be used to predict travel time reliability of the freeway corridor and disseminate it in real time or to assess its historical performance.
Corridor Travel Time Reliability

Figure 4.5 illustrates how travel time reliability of a corridor using the new method varied significantly with segments and departure time. Figure 4.5 points to the strength of the new method since it captures the freeway performance by treating travel time as a continuous variable. This captures the travel time variability experienced by individual drivers over an extended period of departure time.

Figure 4.6 demonstrates low corridor reliabilities. The corridor reliability was estimated using the series system as in Equation 8. For a series system, the system reliability is equal to the product of the reliabilities of its components. The strength of the new methodology is that it was able to capture the fact that the link with the smallest reliability has the biggest effect on system’s reliability. Hence, it was not surprising to see very low corridor reliabilities throughout the evening peak period. The corridor reliability is strongly affected by reliability of its bottlenecks and sections congested upstream of the bottlenecks. As a result, the developed method can be used to assess transportation deficiencies and potential improvements and to evaluate a number of possible alternatives by comparing the current and projected trends in travel time reliability.
Comparison between Reliability Methods

This section compares between the newly developed method and the existing two methods that we ranked highly based on the literature review namely: Florida method and Buffer Time method.

Table 4.2 illustrates application of the Buffer Time reliability method (as defined on page 3) using October 2003 data warehouse sample of I-4 evening commute. The “Buffer Time” was calculated as follows: \( BT = (95\text{th percentile travel time} - \text{average travel time}) \). For example, the average weekday corridor (20 days) “Buffer Time” needed to ensure on-time arrival for 95% of the trips was 11.14 minutes. This means that a traveler should budget an additional 23.05% buffer for a 48.03 minutes average peak trip time for the entire I-4 corridor in order to ensure 95% on-time arrival. Using the same data sample, Table 4.3 demonstrates application of the Florida Reliability method with 5% excess travel time over the median. The Florida method suggested other possible acceptable tolerance thresholds for excess travel time above the median such as 10%, 15%, and 20% in addition to the 5% threshold \([5]\). A statewide (or maybe a national) traveler survey is needed to determine the appropriate percentage. In this Florida method, the reliability statistic was calculated based on the recommended Weibull distribution in ref. \([5]\) as follows:

\[
R(t) = P(x < X + \Delta) = P(x < TT) = 1 - e^{-\left(\frac{T}{\eta}\right)^{\beta}}
\]
The following is a numerical example to illustrate the computations in Table 4.3. The average weekday corridor (20 days) percent of travel that takes no longer than the median travel time to traverse the corridor (46.80 minutes) plus 5% tolerance for additional time had a value of 5.9% (TT = 46.80 X 1.05 = 49.14 minutes).

Figure 4.7 shows a graphical comparison between the three methods when applied to segment (30-42) eastbound I-4 for Wednesdays, October 2003 data sample. In Figure 4.7a, segment 30-42 had a 6.1 minutes travel time at the speed limit (for simplicity this will be called free flow travel time). According to the new method, this segment had at least 95% travel time reliability as long as its travel time does not increase by more than 1.9 minutes (or 31.15% of its free flow travel time). The basic premise of this new method is that it is sensitive to the users’ perspective since it reflects that an increase in segment travel time should always result in less travel time reliability. To illustrate further, if travel time was to increase by about three folds (from 6.1 minutes to 17.5 minutes) then reliability would have decreased down to only 5% as shown in Figure 4.7a.

Figure 4.7b illustrates application of the FDOT method. The median travel time for segment 30-42 was 11.7 minutes and the corresponding travel time reliability for the suggested percentages (of 5%, 10%, 15%, and 20%) were: 58.25%, 65.17%, 71.45%, and 77.01% respectively. According to the Florida method, for segment 30-42 to achieve 95% reliability
at travel time 17.5 minutes the users would have to accept an increase of 48.5% in excess travel time above the median (or an excess of 5.8 minutes above 11.7 minutes). In contrast, the new method estimated reliability for this segment at only 5% for the same travel time of 17.5 minutes, see Figure 4.7a.

Figure 4.7c illustrates application of the Buffer Time method to segment 30-42, which had an average travel time of 12.03 minutes. The “Buffer Time”, or excess time above the average, for this segment was 4.02 minutes. So, according to the Buffer Time method, travel time needed to ensure that 95% of the users will be on time was 16.05 minutes. This is very close to 17.5 minutes, which is the same travel time for which Florida method estimated reliability at 95% for this segment.

To illustrate the new method further, Figure 4.7d shows a graphical comparison between the three methods when applied to an uncongested segment (5-14) eastbound I-4. In Figure 4.7d, segment (5-14) had a 5.71 minutes travel time at the speed limit. Travel time at this segment remained close to free flow travel time during the study period. Accordingly, travel time reliability decreased to 8.94% for an increase of only 0.57 minutes in travel time. Figure 4.7d also illustrates both the FDOT and Buffer Time methods. Segment (5-14) median and mean of travel time were 5.93 minutes and 5.95 minutes respectively. The travel time needed to ensure that 95% of the users will be on time was 6.19 minutes using the Buffer
time method, which is very close to 6.28 minutes (the same travel time for which Florida method estimated reliability at 95% for this segment). This indicates that both Buffer Time and FDOT methods performed better than the new method for uncongested segments. However, it is important to consider the corridor congestion before deciding which method to use. Based on Figures 4.5 and 4.6, the I-4 corridor is mostly congested and the congested segments in series control its reliability.

It is interesting to see that both Florida and Buffer Time methods were close in their reliability estimates, while the new method had significant differences in reliability estimates. Clearly, there is a huge inconsistency in the reliability estimates of the existing methods for congested segments with high travel time range or variability (i.e., segment 30-42). This finding is not counter intuitive because the key difference between the new method and the existing methods is that the new method’s definition of reliability is totally different from the existing methods.

Using a real life data warehouse, we were able demonstrate the vulnerability of the existing reliability methods where the traveler was expected to accept a 95% reliability for segment (30-42) while experiencing travel time three times as much as the free flow travel time. The ultimate judge of the method that should prevail is the traveler, as such traveler surveys are critical to make this determination.
Conclusions

Utilizing a real life dual loop detector transportation data, a new methodology for computing travel time reliability in a freeway corridor has been developed in this paper. The methodology was applied to a section of I-4 in Orlando, Florida. Using the wealth of travel time data available in the I-4 data warehouse, four different distributions were tested: Weibull, Exponential, Lognormal, and Normal. Two evaluation criteria were used in selecting the best-fit distribution: 1) Anderson-Darling (AD) Goodness of Fit statistic, and 2) Error percentages. Based on these criteria, the Lognormal distribution provided the best travel time reliability distribution for the evening peak period of the I-4 corridor (eastbound). Also, this study examined the impact of data sample composition on the estimation of the distribution parameters. Accordingly, it was more efficient to use the same day of the week (e.g., Mondays) in the estimation of travel time reliability for I-4 segments than using mixed data (i.e., first week of the month) because of the significant differences between the weekdays within the same week.

The developed Lognormal distribution was used to estimate segment and corridor travel time reliabilities based on the following definition: “a roadway segment is considered 100% reliable if its travel time is less than or equal the travel time at the posted speed limit.” This definition puts more emphasis on the user’s perspective, and as such is different from reliability definitions of the existing methods (Florida method and Buffer Time method).
The vulnerability of the existing methods, especially when applied to congested freeway segments with high travel time variability, was demonstrated using real life data. These common methods were insensitive to the traveler’s perspective of travel time on the I-4 congested segments. Furthermore, the new method showed high sensitivity to the geographical location that reflects the level of congestion and bottlenecks. A major advantage of the new method above the existing ones is its strong potential in the ability to estimate travel time reliability as a function of departure time. The new method is more appropriate for freeway operations, because it treats travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time.

The newly developed method has a strong potential of being used to compute and predict travel time reliability of the freeway corridor in real time in the RTMC, or it can be used to assess the historical performance of freeway corridors. Also, segment travel time reliability can be used as a tool to provide travelers and freight companies with accurate information about the corridor congestion level to help in planning and scheduling their trips. Future research will focus on traveler surveys to determine the travelers’ perception of travel time reliability and acceptable thresholds of delay above free flow travel time. Using the I-4 data warehouse, we plan to apply this new methodology to peak and off peak periods (e.g., morning and midday) and weekends for different segment lengths of 5, 10, and 20 miles. Finally, this methodology can be easily extended to compute reliability for large-scale real life networks.
References


Table 4.1: Anderson-Darling estimates for travel time reliability distributions

<table>
<thead>
<tr>
<th>Origin</th>
<th>Destination</th>
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<td></td>
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<td></td>
<td></td>
<td>W</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>L</td>
<td>1.4</td>
</tr>
</tbody>
</table>

N: Normal Distribution  
E: Exponential distribution  
W: Weibull Distribution  
L: Lognormal distribution  
M: Mondays of the four weeks in October 2003  
T: Tuesdays of the four weeks in October 2003  
W: Wednesdays of the four weeks in October 2003  
R: Thursdays of the four weeks in October 2003  
F: Fridays of the four weeks in October 2003  
5D: M-F of first week in October 2003  
10D: M-F of first and second week in October 2003  
15D: M-F of first three weeks in October 2003  
20D: M-F of all four weeks in October 2003
Table 4.2: Example application of Buffer Time reliability measure (minutes) using a data sample from the I-4 data warehouse

<table>
<thead>
<tr>
<th>Segment</th>
<th>Distance</th>
<th>M</th>
<th>T</th>
<th>W</th>
<th>R</th>
<th>F</th>
<th>20D</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1: 5 - 14</td>
<td>5.71</td>
<td>0.17</td>
<td>0.48</td>
<td>0.24</td>
<td>0.22</td>
<td>0.38</td>
<td>0.32</td>
</tr>
<tr>
<td>S2: 11 - 22</td>
<td>6.38</td>
<td>0.23</td>
<td>0.43</td>
<td>0.23</td>
<td>0.22</td>
<td>0.30</td>
<td>0.31</td>
</tr>
<tr>
<td>S3: 21 - 30</td>
<td>4.95</td>
<td>0.19</td>
<td>3.19</td>
<td>0.54</td>
<td>1.24</td>
<td>2.60</td>
<td>2.43</td>
</tr>
<tr>
<td>S4: 30 - 42</td>
<td>5.19</td>
<td>3.04</td>
<td>4.99</td>
<td>4.02</td>
<td>2.86</td>
<td>3.23</td>
<td>4.05</td>
</tr>
<tr>
<td>S5: 42 - 52</td>
<td>4.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.62</td>
<td>1.29</td>
<td>0.70</td>
<td>0.82</td>
</tr>
<tr>
<td>S6: 49 - 60</td>
<td>5.83</td>
<td>0.17</td>
<td>2.00</td>
<td>0.12</td>
<td>3.47</td>
<td>0.65</td>
<td>1.92</td>
</tr>
<tr>
<td>S7: 60 - 69</td>
<td>4.50</td>
<td>0.33</td>
<td>1.24</td>
<td>0.62</td>
<td>0.43</td>
<td>1.85</td>
<td>1.29</td>
</tr>
</tbody>
</table>

- Note that number in cells = Excess Travel Time or Buffer Time = 95th percentile travel time – average travel time.
Table 4.3: Example application of the FDOT reliability measure (%) using a data sample from the I-4 data warehouse

<table>
<thead>
<tr>
<th>Segment</th>
<th>Distance</th>
<th>Data levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M</td>
</tr>
<tr>
<td>S1: 5 - 14</td>
<td>5.71</td>
<td>57.0%</td>
</tr>
<tr>
<td>S2: 11 - 22</td>
<td>6.38</td>
<td>94.4%</td>
</tr>
<tr>
<td>S3: 21 - 30</td>
<td>4.95</td>
<td>94.3%</td>
</tr>
<tr>
<td>S4: 30 - 42</td>
<td>5.19</td>
<td>52.3%</td>
</tr>
<tr>
<td>S5: 42 - 52</td>
<td>4.83</td>
<td>69.9%</td>
</tr>
<tr>
<td>S6: 49 - 60</td>
<td>5.83</td>
<td>100.0%</td>
</tr>
<tr>
<td>S7: 60 - 69</td>
<td>4.50</td>
<td>82.7%</td>
</tr>
</tbody>
</table>

Corridor Reliability  | 15.3% | 3.4% | 8.0% | 6.1% | 5.5% | 5.9% |

Note:
- This table uses 5% above median travel time as one of the tolerance thresholds proposed by FDOT, see Shaw and Jackson 2003.
- Number in cells = Segment travel time reliability.
Figure 4.1: I-4 Study segments
Figure 4.2: Travel time distributions (AD and 90 percentile of the absolute error) evaluation criteria
Figure 4.3: The relationship between observed and best-fit distribution
Figure 4.4: Adjusted Lognormal reliability distributions
Figure 4.5: Segments’ travel time reliabilities and departure time
Figure 4.6: I-4 corridor’s travel time reliability versus departure time.
Figure 4.7a. New method

Figure 4.7b. FDOT method

Excess travel time = 1.9 min
Excess travel time = 11.4 min
Reliability at travel time = 17.5 min
Excess travel time = 5.8 min at travel time = 17.5 min with 95% reliability
Figure 4.7c. Buffer Time method

- Excess travel time = 4.02 min at travel time = 16.05 min (close to 17.5 min) with 95% reliability

Figure 4.7d. Segment (5-14)

- New Method excess travel time = 0.57 min (10%) at travel time = 6.28 min (close to 6.19 min in BT)

Figure 4.7: Reliability methods comparison for Wednesdays, Oct. 2003
CHAPTER 5
UTILIZING A REAL LIFE DATA WAREHOUSE TO DEVELOP
FREEWAY TRAVEL TIME RELIABILITY STOCHASTIC MODELS

Abstract

Although travel time reliability has not been a common performance measure, it is very important for providing travelers with accurate route guidance information. A traffic data warehouse with extensive amounts of loop detector traffic counts, and vehicle speeds was utilized to develop a new methodology for estimating travel time reliability of the I-4 corridor in Orlando, Florida. Four different travel time stochastic models: Weibull, Exponential, Lognormal, and Normal were investigated. The developed best-fit stochastic model (Lognormal) can be used to estimate and predict travel time reliability of freeway corridors and report this information in real time to the public through traffic management centers. Analysis of the 4-month data demonstrated that using long segment lengths (e.g., 25 miles) in calculating travel time reliability can be misleading. It is recommended to use shorter segment lengths in the order of 5 miles in calculating travel time reliability for freeway corridors.

The new method was compared to the existing methods (Florida method and Buffer Time
method). The vulnerability of existing methods in estimating reliability of congested segments with high travel time variability was demonstrated using real life data. Unlike the existing methods, which were insensitive to the traveler’s perspective of travel time, the new method showed high sensitivity to the geographical location that reflects the level of congestion and bottlenecks. The major advantage of the new method to practitioners and researchers over the existing methods is its ability to estimate travel time reliability as a function of departure time. As such, it is more appropriate for measuring the performance of freeway operations.

**Keywords:** Reliability, travel time, freeway corridors, stochastic models

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**Introduction**

During the 20\textsuperscript{th} century, transportation programs were focused on the development of the basic infrastructure for the transportation networks. In the 21\textsuperscript{st} century, the focus has shifted to management and operations of these networks (NCHRP, 2003). Reliability measures would play an important role in judging the performance of the transportation system and in evaluating the impact of new Intelligent Transportation Systems (ITS) deployment.

Network reliability theory has been applied extensively in many real-world systems such as computer and communication systems, and power transmission and distribution systems. In this context, reliability is defined as “the probability that an entity will perform its intended
function(s) without failure for a specified length of time under the stated operating conditions at a given level of confidence” (Kececioglu, 1991).

In the transportation field, network reliability has been the subject of considerable international research interest (e.g., see Bell and Cassir, 2000; and Bell and Iida, 2003). The analysis of network reliability involves measuring the ability of the network to meet some expected functional criteria or “tolerance” set by its users, which in turn varies according to the severity and frequency of the underlying ‘non-recurrent’ and ‘recurrent’ causes. Recurrent is generally characterized by everyday rush-hour stop and go conditions, occurring when demand exceeds capacity. Non-recurrent is caused by incidents, maintenance work or construction activities where normal capacity is temporarily reduced, and special events, where peak demand is higher than normal.

Travel time reliability is a challenging subject because there is no single agreed-upon travel time reliability measure. Different researchers have used different definitions of transportation network travel time reliability. For example, in one instant, reliability was defined as the probability that a trip between a given Origin-Destination pair can be successfully made within a specified time interval (Chen et al., 1999; and Yang et al., 2000). Other researchers (Asakura and Kashiwadani, 1991; and Levinson and Zhang, 2001) defined travel time reliability as the probability that a trip can be made successfully within a specified interval of time. They calculated the probability that the travel time will be within a pre-
defined interval (lower and upper bounds). Chen & Recker (2000) assumed travel time reliability as a function of the ratio of the travel times under the degraded and non-degraded states.

In this paper, the definition of travel time reliability is totally different from the existing methods. Unlike the existing methods that defined reliability in terms of travel time variability, the definition of reliability in the new method puts more emphasis on the user’s perspective. The new method has the potential of estimating travel time reliability as a function of departure time. This is accomplished by treating travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time.

This paper is organized as follows: literature review on estimating travel time reliability, a review of the four stochastic models techniques used in this paper, the experimental design of this research study including data collection and preparation, an evaluation of the developed models compared to the existing methods, the paper conclusion and contributions to transportation engineering, and recommendations and suggested future research.
Literature Review

This section is an overview of a number of techniques that have been used in the US to measure travel time reliability in the transportation field.

Percent Variation

Statistically, this is known as the “Coefficient of Variation or CV”. It is calculated as the standard deviation divided by the mean. A traveler can multiply his or her average travel time by the percent variation, and then add that product to his or her average trip time to get the time needed to be on-time about 85 percent of the time (Turner et al., 1996). This measure describes the variability of travel time, but falls short of explaining how well conditions on the corridor meet travelers’ expectations (Shaw and Jackson, 2003).

California Reliability Method

California Transportation Plan (1998) defines reliability as the variability between the expected travel time and the actual travel time (Lomax et al., 2004). The Standard Deviation of Average Trip Time Distribution is used as the reliability index. Segments with insignificant travel time variations from day-to-day “have narrower curves of average trip...
times” and are considered reliable. Since this measure reflects the variation in travel times more than the acceptability of the travel times to the user, it is incomplete.

**Florida Reliability Method**

The Florida Reliability Method was derived from the FDOT’s definition of reliability of a highway system as the percent of travel on a corridor that takes no longer than the expected travel time (the median travel time across the corridor during the period of interest) plus a certain acceptable additional time. This additional acceptable time is a percentage of the expected travel time, and is used to establish the additional time beyond the expected travel time that a traveler would find acceptable. Percentages of 5%, 10%, 15%, and 20% above the expected travel time have been considered but a decision was not finalized (Shaw and Jackson, 2003). Mathematically, reliability $R(t)$ is defined per (FDOT, 2000) as the probability of travel that is no longer than an acceptable travel time, $TT$, as follows:

$$R(t) = P(x < X + \Delta) = P(x < TT)$$

Where:

$X \rightarrow$ The median travel time across the corridor during the period of interest; and

$\Delta \rightarrow$ A percentage of the median travel time during the period of interest
Buffer Time

The buffer time concept may relate particularly well to the way travelers make decisions, it uses minutes of extra travel time needed to allow the traveler to arrive on time (Chen et al., 2003). The buffer time would be the difference between the average and the upper limit of the 95% confidence interval as calculated from the annual average. The main problem is that the public does not readily understand the Buffer Time. Mathematically, the Buffer Time is calculated as follows:

\[
\text{Buffer time} = \left( \frac{95\% \text{ Confidence Travel Time for an Average Trip (in minutes)}}{\text{Average Travel Time (in minutes)}} \right) - 1
\]

By tracking these reliability measures, the Buffer Time and Florida Reliability methods rise above others as the preferred measures, and they seem to resonate with most audiences. However, for these measures, it is not certain what level of reliability (e.g., 85%, 90%, or 95%) should be used.

Previous studies assumed Weibull and Normal distributions for travel time data and used these models to compute reliability but this assumption was never verified with real travel time data. Most of the models have had an empirical rather than theoretical basis for model development. This has a direct impact on the accuracy and transferability of predicting reliability. Also, none of the previous studies compared between the most common existing methods using real life data. Furthermore, none of the existing methods considered the
impacts of segment length on travel time reliability calculations and accuracy. As such, the main goal of this paper is to develop a methodology that will address these major shortcomings.

Specific objectives of this paper include the development of an efficient methodology that can predict the travel time reliability of freeway corridors based on real-time and historical loop detector data. Four statistical stochastic models will be investigated to find the best-fit probability density function using available travel time data. Travel time reliability is then calculated using the best-fit stochastic model and the engineering reliability models that have not been used before in the transportation field. The best-fit travel time reliability model will be implemented on a section of Interstate 400 (I-4) in Orlando, Florida. This section carries large volumes of long distance, inter-regional and intrastate trips.

**Research Framework**

The main goal of this study is to investigate models to forecast travel time reliability. This includes testing the transferability of reliability techniques to the transportation field. This study will focus on four different stochastic models. This section explains the research conceptual plan, the experimental design, and the traffic data that will be used in this paper prior to discussing results and applications.
Research Conceptual Plan

After conducting a thorough literature review it became obvious that there is a need to develop a new methodology for modeling travel time reliability which utilizes the massive traffic data available in freeway data warehouses. Figure 5.1 shows the conceptual plan for modeling freeway travel time reliability. An “experimental design” has been developed to find the best fit travel time stochastic model (Weibull, Exponential, Lognormal and Normal). Anderson-Darling (AD) and the 95th percentile of the absolute error as two evaluation criteria are selected to check the validity of our assumptions regarding the specific stochastic model parameters. Unlike the mechanical components, freeway segments can not have zero travel time. Accordingly, an adjustment of the best-fit stochastic model location parameter is needed. Next, if the calculated travel time for a specific segment on a specific day is less than the acceptable travel time, then the segment is considered 100% reliable. In this paper, the acceptable travel time is defined as travel time at speed limit. In other words, if the segment’s travel time is less than or equal to the free flow travel time or travel time at posted speed limit, then this segment is considered 100% reliable. Otherwise, the developed reliability stochastic models will be used to calculate the segment/corridor travel time reliability as a function of the departure time. The new method results will be compared with existing FDOT and Buffer Time methods. Then, the travel time reliability estimates will be disseminated in real time to the public via advanced traveler information systems to help in pre-trip planning and/or en-route diversion.
The I-4 Traffic Data Warehouse

The Orlando Regional Transportation Management Center (RTMC) monitors 50 miles of I-4 corridor. This paper studied a section of this corridor that is 25 miles long (eastbound direction only) with 25 on-ramps and 26 off-ramps, see Figure 5.3. For simplicity, the section under study will be referred to as “the I-4 corridor” throughout the paper. This section will be called the I-4 corridor in this paper. The I-4 corridor is composed of three lanes in which there are dual loop detectors that are placed at approximately 0.5 miles apart. The loop detectors collect traffic volume, lane detector occupancy, and speed data. The data from these detectors are sent automatically to the RTMC every 30 seconds in a binary format and converted to an ASCII-text format. The University of Central Florida (UCF) used the loop detectors data to update the interactive GIS speed map that UCF developed on the World Wide Web site (www.iflorida.org).

Travel times are derived directly from the speed by considering two consecutive loop detector stations that provide spot speed measurements. In this paper, we will assume that the spot speed estimate is valid half the distance to the adjacent loop detector. And, a link connects between an origin-destination (O-D) pair. The origins and destinations are the major interchanges (from on-ramp to off-ramp end points) where traffic conditions are likely to change. Therefore, travel time between any on and off ramp combination (Origin-Destination) could be calculated as follows (William and Laurence, 2002):
\[ TT = A + \sum_{i=2}^{n-2} \left( \frac{l_{i,i+1}}{2S_i} + \frac{l_{i,i+1}}{2S_{i+1}} \right) + B \]  

(1)

Where:

\[
A = \begin{cases} 
\frac{X_1}{S_2} 
& \text{If } X_1 \leq \frac{l_{1,2}}{2} \\
\frac{l_{1,2}}{2S_2} + \frac{X_1 - \frac{l_{1,2}}{2}}{S_1} 
& \text{Otherwise}
\end{cases}
\]

\[
B = \begin{cases} 
\frac{X_{n-1}}{S_{n-1}} 
& \text{If } X_2 \leq \frac{l_{n-1,n}}{2} \\
\frac{l_{n-1,n}}{2S_{n-1}} + \frac{X_2 - \frac{l_{n-1,n}}{2}}{S_n} 
& \text{Otherwise}
\end{cases}
\]

\( i \) = Detector station \( i \)

\( l_{i,i+1} \) = Distance between detector station \( i \) and \( i+1 \)

\( S_i \) = Spot speed at detector station \( i \)

\( n \) = Number of detector stations

\( X_1 \) = Distance upstream of the first detector in the set

\( X_2 \) = Distance downstream of the last detector in the set

\( TT \) = Travel Time

As with any study that includes a large amount of data, the first step in analysis is to determine which data is useful to the study. Travel time curves for raw versus imputed travel time data are demonstrated in Figure 5.2. The means (standard deviations) of travel times
from station 5 to station 52 (or from E. US 192 to E. SR414) on Tuesday 10/21/03 are 39.91 minutes (15.22 minutes) and 33.94 minutes (3.86 minutes) for raw and imputed data respectively. Similar results were obtained from the analysis of the rest of data. Accordingly, it can be concluded that the imputed data reveals better performance especially during the periods where the raw data is missing or has abnormal values because such outliers could generate biased mean travel time. In this paper, weekdays with observed loop detector raw data (30 seconds intervals) less than 75% of the total daily corridor data were excluded from the analysis. This condition was made to exclude days with significant amount of missing data and to avoid bias in the calculation of mean travel time.

Only imputed data were used in the modeling process in this paper. Travel time between any on and off ramp on I-4 was calculated (see Equation 1) using the real time “filtered” loop speeds stored in the I-4 data warehouse during 2003 (Al-Deek et al., 2004; and Al-Deek and Chilakamarri, 2004).

Data Preparation

A software program was built to query the above specific data. The program was applied to obtain the data of four consecutive months (fall season) from September 1st to December 31st, 2003. The program was written in Visual Basic (VB) and was run in Microsoft Visual Studio. The output comma delimited files (cvs) were dynamically generated and names of
these files were automatically assigned. Data was organized into individual files each containing 24-hours worth of data. For the available four months data during the evening peak (no holidays and no incidents), it was found that there were 50 weekdays valid for analysis in this paper. Each weekday had at least 175,000-loop detector record or 75% of the available daily raw data as mentioned earlier. Preliminary analysis indicated that weekends had a different peak period, and that the number weekdays with incidents during the three peak hours was insignificant (2 weekdays). Therefore, this study will focus on weekdays with no incidents with a sample of 50 weekdays.

In this paper, links are defined as pairs between origins and destinations. For example, an origin started at loop detector ID_5 (On ramp, E. US 192) and the set of destinations (off-ramps) were labeled to the closest loop detector ID (i.e., 14, 22, …, 52) as shown in Figure 5.3. Using Equation (1), the travel time standard deviations and means were calculated every 5 minutes during the evening peak period (from 3:30 PM to 6:30 PM) for the eastbound direction.

**Potential Independent Variables**

The main goal of a forecasting model is to emulate a relationship between the dependent and independent variables. The dependent variable is the travel time. Numerous independent variables were possible from the large amount of data recorded in the I-4 data warehouse.
The independent variables describe the stochastic model (probabilistic distribution type), day of the week, month of the year, and location on I-4. The first independent variable is the “stochastic model”. This variable has four possibilities (Normal, Exponential, Weibull, and Lognormal). We need to find out which one has the best fit with real data. The next independent variable is the traveled distance on I-4, which extends from E. US 192 (Station 5) to E. SR 414 (Station 52). This section was divided into a range of segments with approximately 5, 10, 20, and 25 miles in length as shown in Table 5.1.

In this table, $S_{ij}$ represents the I-4 segments in which ($i = 1, 2, 3$ and 4) refers to the approximate length of the segment (i.e., 5, 10, 20, and 25 miles) respectively and ($j = 1, 2, 3, 4$ and 5) refers to the segment location on I-4 with respect to the loop detector ID_5 (On ramp, E. US 192). For example, $S_{11}$ refers to the first segment of the 5-mile segments group that starts at loop detector ID_5 (On ramp, E. US 192) and ends at loop detector ID_14 (Off ramp, 71-Central Florida Parkway) as shown in Table 5.1 and Figure 5.3. While, $S_{15}$ refers to the last segment of the 5-mile segments group that starts at loop detector ID_42 (On ramp, Ivanhoe Rd) and ends at loop detector ID_52 (Off ramp, 94-E. SR 414) and so on. The next variable is the “day of the week”. This variable had five possible levels of weekday (Monday to Friday) and the levels could be explained as follows: the first level (M) included data from Mondays of the four months analyzed in 2003; the second level (T) included data from Tuesdays of the four months analyzed in 2003, and so on. The last independent
variable represented the “month” under consideration in the analysis sample. This variable had four possible levels (Sep., Oct., Nov., and Dec.). The four levels explored the effect of mixing data in the same sample from different weekdays within the same month.

**ANOVA Test of Significant**

The above independent variables were identified from the available I-4 data warehouse. It is possible that some of the independent variables are not significant or highly related. Thus, it was necessary to perform statistical significance tests on the independent variables using the Analysis Of Variance statistical test (ANOVA) for the proposed dependent variable “travel time”. The null and alternative hypotheses being tested are given below (Mendenhall and Sincich, 1995; and Rencher, 2002).

\[ H_0: \mu_1 = \mu_2 = \ldots = \mu_i \]

\[ H_a: \text{at least two of the } \mu_i \text{'s are different} \]

Where

- \( i \) = the number of samples being compared
- \( \mu_1 \) = the mean travel time of sample “1” when a single factor is applied to population
- \( \mu_i \) = the mean travel time of sample “i” when a single factor is applied to population

An ANOVA table was applied to each independent variable. For example, for the “time of day” independent variable, the ANOVA test compared the five samples (Monday through
Friday) to determine if the underlying mean travel time of each sample was the same (null hypothesis) or significantly different (alternative hypothesis).

The output of the ANOVA table is “F-statistic” and the corresponding “p-value”, which is the smallest level of significance ($\alpha$) at which the null hypothesis (that the five sample travel time means are the same) can be rejected. If the p-value is less than or equal to the level of significance, the null hypothesis is rejected (samples have different travel time means) and the independent variable is significant in terms of travel time for each segment. The ANOVA table was applied to each independent variable and the corresponding “F-statistic” and “p-values” are given in Table 5.2. The ANOVA analysis shows that all of the independent variables are significant ($P < 0.0001$). As a result, the possible combination scenarios of the above variables’ levels is $[4 \times (5 + 4) = 36]$ different scenarios (four “stochastic models”, five “days of the week”, and four “months” of the year) for each freeway segment.

The next step in the paper framework is to review potential stochastic models for estimating travel time reliability. Four different stochastic models will be considered.
Link Travel Time Reliability Stochastic Models

The key in estimating the travel time reliability as a performance measure is in defining the link travel time probability density function (stochastic model). Once the travel time stochastic model of a link is known, then the reliability function of that link can be determined. The analytical methods are preferred due to the high probability of error in using the graphical methods to estimate the stochastic models parameters. The following subsections explain how to use the Least Square Method (LSM) to estimate these parameters. Because Weibull and Lognormal stochastic models are widely used in quality and reliability engineering, we will provide detailed explanations for estimating their parameters. And, we will briefly demonstrate how parameters of the Exponential and Normal models could be estimated.

Weibull Stochastic Model

The Weibull model is a general-purpose reliability stochastic model. Because of its flexible shape and ability to model a wide range of failure rates, Weibull has been used successfully in many applications as a purely empirical model (Kececioglu, 1991; and Tobias and Trindade, 1995). In its most general case, the three-parameter Weibull pdf is defined by:

\[ f(T_i) = \frac{\beta}{\eta} \left( \frac{T_i - \gamma}{\eta} \right)^{\beta-1} e^{-\left( \frac{T_i - \gamma}{\eta} \right)^\beta} \]  

(2)
Where: \( f(T_i) \geq 0, T_i \geq \gamma, \beta > 0, \eta > 0, -\infty < \gamma < \infty \), \((\beta)\) is defined as the shape parameter, \((\eta)\) is the scale parameter, and \((\gamma)\) represents the model location parameter. The Weibull reliability function \( R(T_i) \) is:

\[
R(T_i) = e^{-\left(\frac{T_i - \gamma}{\eta}\right)^\beta} = 1 - F(T_i)
\]  

Taking the double natural logarithm of both sides yields (Kececioglu, 1991; Tobias and Trindade, 1995; and Al-Fawzan, 2000):

\[
\ln \left(\ln \left[1 - F(T_i)\right]\right) = \beta \ln (T_i - \gamma) - \beta \ln (\eta)
\]  

The above is a linear equation, which can be solved as follows:

\[
Y = \beta X + \text{Constant}
\]  

Hence, a straight line will be obtained according to Equations 4 and 5 if \( Y_i = \ln \left[-\ln \left[1 - F(T_i)\right]\right] \) of the segment travel time \((T_i)\) is plotted as a function of \( X_i = \ln (T_i - \gamma) \). The location parameter will equal to the travel time values when \( F(T_i) = 0 \), or when a link is 100% reliable. The Least Square Method (LSM) is used to calculate the estimated scale parameter \((\hat{\eta})\) and shape parameter \((\hat{\beta})\) based on \( X_i \), \( Y_i \) and their mean values \((\bar{X}_i \) and \( \bar{Y}_i \)) as follows:

\[
\hat{\beta} = \left\{ \frac{\left[ n \sum_{i=1}^{n} (X_i)(Y_i) \right] - \left[ \sum_{i=1}^{n} (Y_i) \sum_{i=1}^{n} (X_i) \right]}{\left[ \left\{ \left[ n \sum_{i=1}^{n} (X_i)^2 \right] - \left[ \sum_{i=1}^{n} (X_i) \right]^2 \right\} \right]} \right\}
\]
\[ \hat{\eta} = e^{-\left(\bar{Y} - \hat{\beta} \bar{X}\right)/\hat{\beta}} \] (7)

**Exponential Stochastic Model**

The Exponential distribution is a special case of the Weibull distribution with shape parameter \( \beta = 1 \). As a result, if the travel times of a link are well represented by the exponential distribution with a scale parameter \( 1/\lambda \) and a mean failure rate \( \lambda \), then using Equation 2, the travel time reliability function can be written as:

\[ R(T) = e^{-\lambda(T - \gamma)} \] (8)

The scale parameter can be estimated using Equation 5 as:

\[ \frac{1}{\hat{\lambda}} = \hat{\eta} = e^{-(\bar{Y} - \bar{X})} = e^{-\frac{1}{n} \left( \sum_{i=1}^{n} \ln\left(-\ln[1-F(T_i)]\right) - \sum_{i=1}^{n} \ln(T_i - \gamma) \right)} \] (9)

**Lognormal Distribution**

The Lognormal stochastic model has a flexible probability density and failure rate functions. It has a variety of shapes that can resemble the shapes of the Weibull model (Kececioglu, 1991; and Tobias and Trindade, 1995). This flexibility makes the Lognormal an empirically useful model for right skewed data. The \( pdf \) of the three-parameter Lognormal distribution
\( (\gamma, T_{s0}, \text{ and } \sigma_r) \) is given as:

\[
f(t_i) = \frac{1}{(t_i - \gamma)\sigma_r \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{\ln(t_i - \gamma) - T'}{\sigma_r} \right)^2}
\]  

(10)

Where

\[ f(t_i) \geq 0, t_i \geq \gamma, -\infty < T' < \infty, \sigma_r > 0, -\infty < \gamma < \infty, \ T' = \ln(t_i), \] where ‘T’ is the travel time. The model parameters are as follows: location parameter \( (\gamma) \), scale parameter \( (\sigma_r = \sigma) \), and shape parameter \( (\sigma_r = \sigma) \). The Cumulative Distribution Function \( (CDF) \) can be expressed in terms of the standard normal distribution as:

\[
F(t_i) = \Phi(z) = \Phi \left[ \frac{\ln(t_i - \gamma) - \ln(T_{s0})}{\sigma} \right]
\]  

(11)

Then, the inverse of the standard normal CDF function \( (\Phi) \) is applied to derive an equation that is linear in the unknown parameters as follows (Kane, 1982; Kececioglu, 1991; and Tobias and Trindade, 1995):

\[
\Phi^{-1}(F(T')) = \left( \frac{\ln(t_i - \gamma) - \ln(T_{s0})}{\sigma} \right)
\]  

\[
\ln(t_i - \gamma) = \ln(T_{s0}) + \sigma \Phi^{-1}(F(t_i))
\]  

(12)

The above is a linear equation, which can be solved similar to the Weibull derivations, the location parameter will equal to travel time when \( F(T) = 0 \). Then, the scale and shape parameters can be obtained as follows:
\[
\hat{\sigma} = \left\{ \frac{n \sum_{i=1}^{n} (X_i)(Y_i) - \left( \sum_{i=1}^{n} Y_i \right) \left( \sum_{i=1}^{n} X_i \right)}{\left[ n \sum_{i=1}^{n} (X_i)^2 \right] - \left( \sum_{i=1}^{n} X_i \right)^2} \right\}
\]

(13)

\[
\ln(T_{50}) = (\bar{Y} - \hat{\sigma} \bar{X}) \quad \text{or} \quad T_{50} = e^{(\bar{Y} - \hat{\sigma} \bar{X})}
\]

(14)

Then, the reliability function can be written as:

\[
R(T_i) = 1 - F(T_i) = 1 - \Phi \left\{ \frac{\ln(T_i - \gamma) - \ln(T_{50})}{\hat{\sigma}} \right\}
\]

(15)

**Normal Distribution**

The normal distribution is the logarithm of the lognormal distribution with location parameter \((\gamma = 0)\), mean or scale parameter \((\mu = \ln(T_{50}))\) and standard deviation or shape parameter \((\sigma = \sigma_T)\). The reliability function can be written as:

\[
R(T_i) = 1 - F(T_i) = 1 - \Phi \left\{ \frac{T_i - \hat{\mu}}{\hat{\sigma}} \right\}
\]

(16)

The model parameters can be estimated using Equations 14 and 15.

**Goodness-of-Fit Test**

To check the validity of our assumptions regarding the specific travel time stochastic model (Normal, Exponential, Weibull, or Lognormal), the Goodness of Fit (GoF) tests that are
based on either the cumulative distribution function \((CDF)\) such as \textit{Anderson-Darling} (AD)
and the \textit{Kolmogorov-Smirnov} (KS) testes or the probability density function \((pdf)\) such as the
Chi-Square test can be used. We have selected AD because it is among the best distance
tests for small and large samples, and various statistical packages are widely available for
this AD test (Shimokawa and Liao, 1999). Anderson-Darling statistic is a weighted squared
distance from the plotted points to the fitted line with larger weights in the tails of the
distribution with the null hypothesis:

\[ H_0: \text{The data followed the specified distribution.} \]
\[ H_a: \text{The data did not follow the specified distribution.} \]

Also, the 95\textsuperscript{th} percentile of the absolute errors, which were calculated by comparing the
predicted and the actual distribution, is used as another evaluation criterion to assess the
assumed distribution parameters.

\textbf{System Travel Time Reliability}

In a series configuration, as in the freeway corridor, a failure of any individual link causes an
overall system failure. Readers are refereed to our paper (Al-Deek and Emam, 2006) for
more details. Mathematically, the reliability of the corridor is then given by:
\[ R_S = P(X_1)P(X_2)...P(X_n) = \prod_{i}^{n} P(X_i) = \prod_{i}^{n} R(X_i) = \prod_{i}^{n} R_i \]  \hspace{1cm} (17)

Where: \( R_s \) = Reliability of the system, \( X_i \) = Event of link \( i \) being operational, and \( P(X_i) \) = Probability that link \( i \) is operational. For example, if all the components have the same reliability (\( R(x) = 0.95 \)), then the system reliability of a series configuration of (\( n = 10 \)) components will be:

\[ R_S = \prod_{i}^{n} R_i = 0.95^{10} \approx 0.60 \]

Hence, the system reliability of a series configuration is much lower than 0.95. This ends the reliability analysis framework proposed in this paper. Now, we move to the model application of this developed framework to the I-4 corridor and data warehouse previously described in pages 110 through 115.

**Model Application**

Using this I-4 data warehouse we were able to come up with estimates of the travel time stochastic models parameters. Once the model with the “best” fit of the segment was selected, then an adjustment was needed. This adjustment must reflect that 100% travel time reliability does not start right at zero travel time. It is unrealistic that any highway segment can be traversed in zero seconds no matter how fast the vehicles are. Also, the public has a
perception of acceptable travel time threshold at which 100% travel time reliability is achieved. The logical assumption is to consider the road segment to be 100% reliable if its travel time is less than or equal to an upper threshold. We choose this upper threshold for each segment to be equal to the segment length divided by the speed limit. By doing this we assume that the public will be completely satisfied if traffic conditions allow them to travel the roadway facility at the speed limit. Such assumption can be verified with traveler survey.

**Segment Travel Time Stochastic Model**

The *LSM* was used to fit the data to the theoretical travel time stochastic models (Weibull, Exponential, Lognormal, or Normal) as described earlier. The travel time data was used to produce a number of stochastic models. Once the stochastic models were developed, the Anderson-Darling goodness-of-fit test was calculated to test the assumption that the travel time follows the four tested models. Figure 5.4 shows the percentages of the fitted models that have *AD* values less than 1.5. It is obvious that as long as data was gathered from different days of different months the estimation of parameters got worse as evident in the large *AD* statistic, which has a negative impact on estimation accuracy. The null hypothesis is rejected at 99% confidence level for all *AD* exceeding the appropriate critical value (1.5) as in D'Agostino and Stephens, 1986.

In Figure 5.4, we found that on average 50.0% or more of the Lognormal models had *AD*
values less than the critical value (1.5) for the weekdays data. The aforementioned value dropped to 16.7% for samples with mixed weekdays (e.g., September) and reached 0.0% for the “all days” sample (50 weekdays). The results demonstrated that using data for the same weekdays (e.g., Mondays) yielded better results compared to mixing data for different weekdays within the same month or from different months in the same sample. Also, the exponential model failed to meet this criterion for all scenarios.

The second criterion was the estimated error percentages, which were calculated by comparing the predicted and the actual distribution. Among the analyzed scenarios, the 95th percentile of the absolute errors of the Lognormal models were less than 5.78% compared to 9.03%, 14.10%, and 23.52% of the Weibull, Normal, and Exponential models respectively, see Figure 5.4. Consequently, the Lognormal proved to be the best stochastic model that fit travel time, especially for the day of the week samples (Monday through Friday). This was followed by the Weibull distribution. The Exponential distribution had the highest 95th percentile (23.53%) and the highest AD values (none of the AD values were below the 1.5 threshold), so it was ranked lowest.

Based on these results, the rest of the paper analysis will only focus on the first five categories (or five levels) of data that represent weekdays (Mondays, Tuesdays, ..., and Fridays). This leads to “60” Lognormal model scenarios (5 weekdays x 12 segments).
Spatial Correlation in Travel Time

Based on observations of the travel time data available in the UCF data warehouse, it is inappropriate to assume that segment travel times are generally independent. For example, the correlation of travel times on segments $S_{11}$ and $S_{12}$ is very obvious with a correlation coefficient of 0.70 and p-value less than 0.0001 (see Table 5.3 for Mondays, 2003). Table 5.3 indicates that the correlation coefficients between travel times on these two adjacent segments are significant. However, for the rest of the segments that are adjacent to each other ($S_{12}$ and $S_{13}$, $S_{13}$ and $S_{14}$, $S_{14}$ and $S_{15}$), correlation is insignificant. Note that although the correlation coefficient between $S_{12}$ and $S_{13}$ is significant, it is weak correlation (only 0.16795). The analysis was based on computing and testing correlation coefficients for each pair of segments, using the data points available for each pair. The Pearson correlation coefficient (product-moment coefficient of correlation) was used in this analysis. It measures the strength of a linear relationship between a pair of two variables.

The result is that for these travelers that traveled segments ($S_{11}$ and $S_{12}$), it would be more accurate to calculate the travel time mean and variance for segment $S_{21}$, that starts at loop detector ID_5 (On ramp, E. US 192) and ends at loop detector ID_22 (Off ramp, 75A-Universal Drive) as shown in Table 5.1, instead of summing the mean and variance of segments ($S_{11}$ and $S_{12}$) without consideration of their travel time correlation. Note that segment $S_{21}$ includes segments $S_{11}$ and $S_{12}$ as part of its length.
Travel Time Reliability Stochastic Models

The reliability function $R(t)$, of a system at time $t$ is the cumulative probability that the system has not failed from 0 to $t$. This can be represented as:

$$R(t) = P\{T \geq t\} = 1 - \int_0^t f(t) dt = 1 - F(t), \quad -\infty < t < \infty$$  \hspace{1cm} (18)

Accordingly, the best (Lognormal) travel time reliability model in Equation (16) was compared to the Empirical Cumulative Distribution Reliability Function (ECDRF). The ECDRF supplies immediate information regarding the shape of the underlying distribution, outliers, and robust information on location and dispersion. The ECDRF of a sample $\{T_i, i = 1, 2, 3, ..., n\}$ is defined as the following function:

$$R_n = 1 - F_n = 1 - \frac{\#(T_i \leq t)}{n}, \quad -\infty < t < \infty$$  \hspace{1cm} (19)

Where $\#(T_i \leq t)$ is read, the number of $(T_i$’s) less than or equal to $(t)$ for the sample size $(n)$.

Theoretical Versus Empirical Reliability Distributions

Figure 5.5 shows plots of 3 out of the 12 analyzed segments to examine the convergence between ECDRF and the Lognormal stochastic models and the similarities among the weekdays (i.e. Mondays, Tuesdays, …, and Fridays) for the same segment. Clearly, the two plots (ECDRF and the Lognormal stochastic models) are almost identical for the same weekday which means that there are no significant differences between them.
After the visual inspection, the t-statistical test was used to determine if the two means of the Empirical and the best-fit Lognormal stochastic models are equal assuming equal variances. The results showed that there is no significant difference at 95% confidence level between the mean of the two distributions (Lognormal versus ECDRF) for all segments (i.e., \( P > 0.05 \)). It can be concluded that the Lognormal models replicate the ECDRF reliability distributions at the 95% confidence level.

Furthermore, the t-statistical test was used to see if there was a statistically significant difference between the weekdays and hence requiring different parameter estimates (models) for each weekday data group (i.e., Mondays, Tuesdays, ..., and Fridays). Using the t-student test (two samples with unequal variances) after taking the logarithm of the travel time, because the logarithm of a Lognormal is Normal, it was found that there was a significant difference (i.e., \( P < 0.05 \)) between the weekdays (Mondays through Fridays) in most of the segments (e.g., \( S_{13}, S_{22}, \) and \( S_{41} \)) as shown in Figure 5.5. Consequently, it was imperative to compute the appropriate estimates of the Lognormal model parameters based on the day of the week for each segment.

**Segment Travel Time Reliability**

Unlike the mechanical equipments, it is unrealistic that any freeway segment can be traversed
in zero seconds no matter how fast the vehicles are. And, an adjustment of the model location parameter was needed to accurately estimate the travel time reliability and to achieve the following definition “a roadway segment is considered 100% reliable if its travel time is less than or equal to the travel time at the posted speed limit.” The threshold or the location parameter ($\gamma$) had to be adjusted to reflect the acceptable travel time level (travel time at posted speed limit), see Figure 5.6. The adjusted location parameter can be calculated as a function of the acceptable upper limit of travel time and the corresponding reliability. Equation 13 can be re-written as follows:

$$\sigma \Phi^{-1}(1 - R(T)) = \ln(t - \gamma) - \ln(T_{50}) \Rightarrow \ln(t - \gamma) = \ln(T_{50}) + \sigma \Phi^{-1}(1 - R(T))$$

Substitute for $t = \text{distance divided by speed limit}$ and consider that $R(T)$ is 100%, we get:

$$\ln(t - \gamma) = \ln(T_{50}) - 3\sigma \Rightarrow \gamma = t - e^{\ln(T_{50}) - 3\sigma}$$

The reason for substituting $\Phi^{-1}[(1 - R(T))] \approx -3$ is that under a normal curve, approximately 99% of test observations fall within three standard deviations. Similarly, the adjusted location parameter $\gamma$ can be calculated for the other three distributions (Weibull, Exponential, and Normal). In Figures 5.5 and 5.6, it is observed that there are large variations between weekdays in travel time reliability. Differently, the travel times had different patterns among the weekdays. Therefore, different models for each weekday (e.g., Mondays) were developed for each segment.
Travel Time Reliability and Departure Time

The developed Lognormal models were used to estimate the travel time reliability as a function of the departure time for each weekday (Mondays through Fridays) for the 12 analyzed segments. These segments were categorized based on their mean travel speed as uncongested segments (e.g., S₁₁, S₁₂, and S₂₁) and congested segments (e.g., S₁₃, S₁₄, S₁₅, S₂₂, S₂₃, S₂₄, S₃₁, S₃₂, and S₄₁). The two congestion categories were classified based on the variation in loop detectors speed and how close their observed speeds to the speed limits during the peak hours.

The uncongested segments’ (e.g., S₂₁) travel time reliability of the weekdays had the same pattern and varies by no more than 20% among the weekdays as shown in Figure 5.7. This depicted the sensitivity of model for any minor travel time changes in such segments and resulted in continuous fluctuation in the travel time reliability pattern with the departure time. At the end of the peak, this fluctuation decreased to be around 10%. On the other hand, the congested segments (e.g., S₁₄ and S₃₁) had an obvious peak (that started between 17:15 and 17:30) and in which the travel time reliability dropped to less than 40% as shown in Figure 5.7.

As expected, the longer the segment, the higher the variation in the travel time reliability among the weekdays. For example, there is a noticeable difference in the fluctuation of the travel time reliabilities prior to 17:00 for segment S₁₄ compared to S₃₁ among the weekdays.
at the same departure time as shown in Figure 5.7. In this case, segment (S_{31}) is about 20-miles and composed of uncongested and congested segments (S_{21}, S_{13}, and S_{14}), while segment (S_{14}) is only 5-miles.

**Benefits of the New Method to Practitioners and Researchers**

The above results underscore the fact that the developed models are appropriate for evaluating freeway operations performance. They capture the travel time variability experienced by individual travelers over an extended period of time. They can be used to calculate and predict travel time reliability of the freeway segments or corridor in real time or to assess its historical performance. In the following pages, we demonstrate the benefits of the new method and compare it to the existing methods.

**Segment Travel Time Reliability**

Figure 5.8 illustrates how travel time reliability of a segment (using the new methodology) varied significantly with the day of the week, segment location and departure time. It is obvious that, for some segments, the travel time reliability at 18:30 (end of peak) is higher than the corresponding values at 17:30 (peak). For example, segment (S_{14}) travel time reliability ranges from 31% to 41% at 17:30 compared to 70% to 91% at 18:30 over the weekdays. This information could be disseminated to roadway users during their pre-trip planning to help them make a decision about their departure time. Also, the travel time
reliability could be disseminated in-trip through the cell phones, Radio or Changeable Message Signs (CMS) to eliminate the freeway users’ anxiety about the unknown, guide them to the diversion alternatives, and give them the probability to reach their destinations.

**Corridor Travel Time Reliability**

Figure 5.9 illustrates and points to the strength of the new methodology since it captures the freeway performance by treating travel time as a continuous variable. The corridor reliability was estimated using the series system as in Equation 17. The corridor reliability is equal to the product of the reliabilities of its components. This means that the link with the smallest reliability will have the biggest effect on corridor’s reliability. However, the travel time reliability of the corridor as a function of the departure time has the same trend, but it significantly depends on the segment length. The smaller the segment, the lower the corridor travel time reliability and the more accurate the estimated reliability is as shown in Figure 5.9.

It was not surprising to see very low corridor reliabilities throughout the evening peak period with the 5-mile segments compared to the 25-mile segment. For the 5-mile segments, the freeway users judge each segment individually and any increase in travel time particularly on the uncongested segments has significant effect on the overall corridor travel time reliability. Accordingly, the corridor travel time reliability was found to be less than 20% from 17:15 to 18:15 during the peak period. This information is more appropriate for the freeway
operations as a microscopic performance measure of the freeway corridor. On the other hand, the corridor travel time reliability was found to be at least 40% during the same period using the 25-mile segment as shown in Figure 5.9. As such, using long segments in calculating travel time reliability can result in misleading information. Long segments (i.e., 25 miles) may show that the corridor travel time is reliable, while short segments (i.e., 5 miles) may indicate that the corridor is unreliable due to severe congestion. However, using long segments may be more appropriate for planning purposes as a macroscopic evaluation of the freeway corridor, especially in the absence of detailed data for smaller segments.

Evidently, the travel time reliability is strongly dependent on the length of the analyzed segments and it is highly affected by the reliability of its bottlenecks and sections congested upstream of the bottlenecks. We were able to show the high discrepancy in the corridor travel time reliability due to high sensitivity to segment length. Therefore, it is recommended to calculate the travel time reliability for smaller segments and then calculate the corridor reliability using the series equation for performance evaluation purposes.

**Comparison between Reliability Methods**

This section compares between the newly developed method and the existing two methods (Florida method and Buffer Time method) that are ranked highly based on the literature review.
Table 5.4 illustrates application of the Buffer Time reliability method (as defined in page 108) using the 4-months data sample of I-4 evening commute. The “Buffer Time” was calculated as follows: \( BT= (95^{th} \text{ percentile travel time} - \text{ average travel time}) \). For example, the average weekday corridor (Tuesdays) “Buffer Time” needed to ensure on-time arrival for 95% of the trips was 13.73 minutes (based on the 5 mile segments). This means that a traveler should budget an additional 38.6% buffer for a 35.59 minutes average peak trip time for the 25-miles on the I-4 corridor in order to ensure 95% on-time arrival. Using the same data sample, Table 5.5 demonstrates application of the Florida Reliability method with 5% excess travel time over the median (34.56 minutes). A statewide (or maybe a national) traveler survey is needed to determine the appropriate percentage. In this Florida method, Shaw and Jackson (2003) recommended the Weibull distribution for the calculation of the reliability statistic as follows:

\[
R(t) = P(x < X + \Delta) = P(x < TT) = 1 - e^{-(TT/\eta)^\beta}
\]

Where \( \beta \) is defined as the shape parameter and \( \eta \) is the scale parameter. The rest of the parameters in this equation were defined on page 109. The following is a numerical example to illustrate the computations in Table 5.5. The average weekday (Tuesdays) percent of travel that takes no longer than the median travel time to traverse the 25-miles of the I-4 corridor (34.56 minutes) plus 5% tolerance for additional time (\( TT = 34.56 \times 1.05 = 36.31 \) minutes) had a value of 13.73%. In other words, 13.73% of the freeway commuters would
travel the 25-mile segment in less than 36.31 minutes.

Similar to the new developed method, the corridor travel time reliability (25-miles) calculated in both methods using the 5-mile segments are more accurate compared to using the full length of the 25 miles as one long segment. Again, the smaller segment is, the more accurate the corridor travel time reliability will be.

Figure 5.10 shows a graphical comparison between the three methods when applied to 5-mile segment (S_{15}) eastbound I-4 for Thursdays, 2003 data sample. This segment had a 5.3 minutes travel time at the speed limit (for simplicity this will be called free flow travel time) as shown in Figure 10a. According to the new method, this segment has at least 95% travel time reliability as long as its travel time does not increase by more than 1.53 minutes (or 28.87% of its free flow travel time).

The basic premise of this new method is that it is sensitive to the users’ perspective since it reflects that an increase in segment travel time should always result in less travel time reliability. To illustrate further, if travel time was doubled (from 5.3 to 11.0 minutes) then reliability would have decreased down to only 20.1% as shown in Figure 5.10a.

Figure 5.10b illustrates application of the FDOT method. The median travel time for segment (S_{15}) was 7.5 minutes and the corresponding travel time reliability for the suggested
percentages (of 5%, 10%, 15%, and 20%) were: 57.6%, 64.4%, 70.6%, and 76.2% respectively. According to the Florida method, for segment (S15) to achieve 95% reliability at travel time 11.0 minutes the users would have to accept an increase of 46.7% in excess travel time above the median (or an excess of 3.5 minutes above 7.5 minutes). In contrast, the new method’s estimated reliability for this segment is only 20.1% for the same travel time of 11.0 minutes.

Figure 5.10c illustrates application of the Buffer Time method to segment (S15), which had an average travel time of 7.3 minutes. The “Buffer Time”, or excess time above the average, for this segment was 3.80 minutes or about 50% in excess travel time above the average. So, according to the Buffer Time method, travel time needed to ensure that 95% of the users will be on time was 11.1 minutes. This is very close to 11.0 minutes, which is the same travel time for which Florida method estimated reliability at 95% for this segment. This indicates that both Buffer Time and FDOT methods performed similarly. At least 47% tolerance above the mean or the median is required to achieve the 95% on time arrival. Similar results were obtained from the 10-mile segment (e.g., S22) and the corridor analysis (25-mile segment) as shown Figure 5.11 and Figure 5.12 respectively.

It is interesting to see that both Florida and Buffer Time methods were close in their reliability estimates. Clearly, there is a huge discrepancy between the reliability estimates of the new method and the existing methods used in this numerical example. This finding is not
counterintuitive because the key difference between the new method and the existing methods is that the new method’s definition of reliability is totally different than the existing methods. However, using a real life data warehouse, we were able to illustrate the vulnerability of the existing reliability methods where the traveler was expected to accept a 95% reliability while experiencing a congested link with travel time more than twice the free flow travel time. The ultimate judge of which method should prevail is the traveler. As such, traveler surveys are critical to make this determination.

Conclusions

A new methodology for estimating travel time reliability in a freeway corridor has been developed in this paper utilizing a real life traffic data warehouse. A four-month data sample was studied. The methodology was applied to a section of I-4 in Orlando, Florida. Four different stochastic models were tested: Weibull, Exponential, Lognormal, and Normal. Two evaluation criteria were used in selecting the best-fit model: 1) Anderson-Darling (AD) Goodness of Fit statistic, and 2) 95th error percentages. Based on these criteria, the Lognormal model provided the best fit of travel time reliability for the evening peak period of the I-4 corridor (eastbound). Also, it was more efficient to use the same day of the week (e.g., Mondays) in estimating travel time reliability for I-4 segments than using mixed data (i.e., entire month of October) because of the significant differences between the weekdays within the same month.
The developed Lognormal model was used to estimate segment and corridor travel time reliability based on the following definition: “a roadway segment is considered 100% reliable if its travel time is less than or equal to the travel time at the posted speed limit.” This definition puts more emphasis on the user’s perspective, and as such is different from reliability definitions of the existing methods (Florida method and Buffer Time method). The vulnerability of the existing methods was demonstrated using real life data as compared to the new method.

The developed travel time reliability model was dependent on the length of the analyzed segments. In the lack of detailed travel time data of smaller segments, longer segments can be used to estimate freeway reliability, but this is only appropriate for planning purposes. On the other hand, and if detailed data is available, then smaller segments should be used to evaluate travel time reliability of freeway corridors for the purposes of freeway operations. Furthermore, the new method showed high sensitivity to the geographical location which reflects the level of congestion and bottlenecks. A major advantage of the new method above the existing ones is its strong potential in the ability to estimate travel time reliability as a function of departure time. The new method is more appropriate for freeway operations, because it treats travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time.
The newly developed method has a strong potential of being used to compute and predict travel time reliability of the freeway corridor in real time, or assess the historical performance of freeway corridors. Future research will focus on traveler surveys to determine the travelers’ perception of travel time reliability and acceptable thresholds of delay above free flow travel time. Also, we plan to apply this new methodology to peak and off peak periods (e.g., morning and midday) using the I-4 traffic data warehouse. Finally, the methodology used in this study may be transferable to other similar freeway surveillance data for derivation of a customer level of service. The new method can be extended to compute reliability for large-scale real life networks.

References


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<th>Group (length)</th>
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<th>Destination (Loop ID)</th>
<th>Distance (miles)</th>
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Table 5.2: Independent variable significant test results

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<th>Day of the week (M, T, W, R &amp; F)</th>
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<td>&lt;.0001</td>
</tr>
<tr>
<td>S13</td>
<td>24.08</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S14</td>
<td>40.29</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S15</td>
<td>13.24</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S21</td>
<td>119.41</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S22</td>
<td>39.52</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S23</td>
<td>25.31</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S24</td>
<td>46.20</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S31</td>
<td>43.22</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S32</td>
<td>44.46</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>S41</td>
<td>294.23</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>
Table 5.3: Correlation between I-4 Eastbound segments on Mondays, 2003

Pearson Correlation Coefficients, N = 480

Prob > |r| under H0: ρ=0

<table>
<thead>
<tr>
<th>Segment</th>
<th>S_{11}</th>
<th>S_{12}</th>
<th>S_{13}</th>
<th>S_{14}</th>
<th>S_{15}</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_{11}</td>
<td>1</td>
<td>0.70058 &lt;.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_{12}</td>
<td>0.70058 &lt;.0001</td>
<td>1</td>
<td>0.16795 0.0002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_{13}</td>
<td>0.16795 0.0002</td>
<td>1</td>
<td>0.12072 0.0081</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_{14}</td>
<td>0.12072 0.0081</td>
<td>1</td>
<td>0.05605 0.2203</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_{15}</td>
<td></td>
<td>0.05605 0.2203</td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$r$: Parson Correlation Coefficient (Sample)

$\rho$: Population Correlation Coefficient
Table 5.4: Example application of Buffer Time reliability measure (minutes) using a data sample from the I-4 data warehouse

<table>
<thead>
<tr>
<th>Segment</th>
<th>Distance (miles)</th>
<th>M</th>
<th>T</th>
<th>W</th>
<th>R</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>S11: 5 - 14</td>
<td>5 (5 – miles)</td>
<td>8.73</td>
<td>13.73</td>
<td>14.78</td>
<td>12.17</td>
<td>12.57</td>
</tr>
<tr>
<td></td>
<td>10 (10 – miles)</td>
<td>10.70</td>
<td>9.78</td>
<td>13.83</td>
<td>11.46</td>
<td>9.16</td>
</tr>
<tr>
<td></td>
<td>25 (25 – miles)</td>
<td>7.45</td>
<td>7.20</td>
<td>10.54</td>
<td>10.19</td>
<td>6.57</td>
</tr>
</tbody>
</table>

Data levels

<table>
<thead>
<tr>
<th>Segment</th>
<th>Distance</th>
<th>M</th>
<th>T</th>
<th>W</th>
<th>R</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>S11: 5 - 14</td>
<td>5.71</td>
<td>0.35</td>
<td>0.35</td>
<td>0.93</td>
<td>0.34</td>
<td>0.37</td>
</tr>
<tr>
<td>S12: 11 - 22</td>
<td>6.38</td>
<td>0.27</td>
<td>0.23</td>
<td>0.77</td>
<td>0.41</td>
<td>0.29</td>
</tr>
<tr>
<td>S13: 21 - 30</td>
<td>4.95</td>
<td>0.34</td>
<td>3.52</td>
<td>3.95</td>
<td>2.75</td>
<td>3.43</td>
</tr>
<tr>
<td>S14: 30 - 42</td>
<td>5.19</td>
<td>4.76</td>
<td>5.87</td>
<td>5.36</td>
<td>5.26</td>
<td>6.83</td>
</tr>
<tr>
<td>S15: 42 - 52</td>
<td>4.83</td>
<td>3.02</td>
<td>3.76</td>
<td>3.78</td>
<td>3.41</td>
<td>1.65</td>
</tr>
<tr>
<td>S21: 5 - 22</td>
<td>10.14</td>
<td>0.47</td>
<td>0.43</td>
<td>1.38</td>
<td>0.57</td>
<td>0.56</td>
</tr>
<tr>
<td>S22: 21 – 42</td>
<td>10.14</td>
<td>7.21</td>
<td>5.60</td>
<td>8.67</td>
<td>7.48</td>
<td>6.95</td>
</tr>
<tr>
<td>S23: 11 – 30</td>
<td>10.84</td>
<td>0.66</td>
<td>3.68</td>
<td>4.51</td>
<td>2.70</td>
<td>3.40</td>
</tr>
<tr>
<td>S24: 30 – 52</td>
<td>10.02</td>
<td>7.26</td>
<td>6.52</td>
<td>7.17</td>
<td>7.11</td>
<td>5.15</td>
</tr>
<tr>
<td>S31: 5 - 42</td>
<td>19.79</td>
<td>7.23</td>
<td>5.59</td>
<td>9.58</td>
<td>7.28</td>
<td>6.46</td>
</tr>
<tr>
<td>S32: 11 – 52</td>
<td>20.86</td>
<td>7.68</td>
<td>7.09</td>
<td>10.30</td>
<td>10.03</td>
<td>6.66</td>
</tr>
<tr>
<td>S41: 5 - 52</td>
<td>5.83</td>
<td>7.45</td>
<td>7.20</td>
<td>10.54</td>
<td>10.19</td>
<td>6.57</td>
</tr>
</tbody>
</table>
Table 5.5: Example application of the FDOT reliability measure (%) using a data sample from the I-4 data warehouse

<table>
<thead>
<tr>
<th>Segment</th>
<th>Distance</th>
<th>M</th>
<th>T</th>
<th>W</th>
<th>R</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>S11: 5 - 14</td>
<td>5.71</td>
<td>90.82%</td>
<td>91.70%</td>
<td>73.77%</td>
<td>89.10%</td>
<td>89.50%</td>
</tr>
<tr>
<td>S12: 11 - 22</td>
<td>6.38</td>
<td>94.00%</td>
<td>97.84%</td>
<td>78.25%</td>
<td>86.10%</td>
<td>95.47%</td>
</tr>
<tr>
<td>S13: 21 - 30</td>
<td>4.95</td>
<td>74.74%</td>
<td>52.36%</td>
<td>39.22%</td>
<td>66.17%</td>
<td>43.17%</td>
</tr>
<tr>
<td>S14: 30 - 42</td>
<td>5.19</td>
<td>88.72%</td>
<td>57.12%</td>
<td>54.61%</td>
<td>60.29%</td>
<td>15.77%</td>
</tr>
<tr>
<td>S15: 42 - 52</td>
<td>4.83</td>
<td>56.46%</td>
<td>51.16%</td>
<td>52.80%</td>
<td>52.68%</td>
<td>62.26%</td>
</tr>
<tr>
<td>S21: 5 - 22</td>
<td>10.14</td>
<td>95.08%</td>
<td>97.57%</td>
<td>76.45%</td>
<td>89.60%</td>
<td>94.22%</td>
</tr>
<tr>
<td>S22: 21 – 42</td>
<td>10.14</td>
<td>53.53%</td>
<td>59.38%</td>
<td>52.23%</td>
<td>63.96%</td>
<td>63.32%</td>
</tr>
<tr>
<td>S23: 11 – 30</td>
<td>10.84</td>
<td>81.76%</td>
<td>68.08%</td>
<td>51.60%</td>
<td>69.28%</td>
<td>57.49%</td>
</tr>
<tr>
<td>S24: 30 – 52</td>
<td>10.02</td>
<td>52.94%</td>
<td>58.54%</td>
<td>53.61%</td>
<td>61.09%</td>
<td>63.39%</td>
</tr>
<tr>
<td>S31: 5 - 42</td>
<td>19.79</td>
<td>59.15%</td>
<td>65.67%</td>
<td>55.10%</td>
<td>63.94%</td>
<td>67.77%</td>
</tr>
<tr>
<td>S32: 11 – 52</td>
<td>20.86</td>
<td>58.59%</td>
<td>63.00%</td>
<td>54.43%</td>
<td>63.59%</td>
<td>68.15%</td>
</tr>
<tr>
<td>S41: 5 - 52</td>
<td>5.83</td>
<td>60.17%</td>
<td>64.62%</td>
<td>55.55%</td>
<td>64.47%</td>
<td>69.74%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Corridor Reliability</th>
<th>(5 – miles)</th>
<th>(10 – miles)</th>
<th>(25 – miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>31.97%</td>
<td>28.74%</td>
<td>21.40%</td>
</tr>
<tr>
<td></td>
<td>13.73%</td>
<td>29.64%</td>
<td>29.92%</td>
</tr>
<tr>
<td></td>
<td>6.53%</td>
<td>21.08%</td>
<td>16.13%</td>
</tr>
<tr>
<td></td>
<td>16.13%</td>
<td>30.19%</td>
<td>37.14%</td>
</tr>
<tr>
<td></td>
<td>3.62%</td>
<td>37.14%</td>
<td>69.74%</td>
</tr>
</tbody>
</table>

Note: This table uses 5% above median travel time as one of the tolerance thresholds proposed by FDOT, (see Shaw and Jackson, 2003)
Figure 5.1: Conceptual plan
Figure 5.2: Comparison of travel times for raw and imputed data during the PM peak hours
Figure 5.3: I-4 corridor segments in the city of Orlando, Florida
Figure 5.4: Travel time distributions evaluation criteria (AD and 95 percentile of the absolute error)
Figure 5.5: The relationship between empirical cumulative distribution reliability and best-fit distributions
Figure 5.6: Adjusted Lognormal reliability distributions
Figure 5.7: Travel time reliability and departure time
Figure 5.8: Travel time reliability and departure time for all segments

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Figure 5.9: I-4 corridor’s travel time reliability versus departure time
Figure 5.10: Comparison of the reliability methods for segment S15 (5-mile) for Thursdays, 2003
Figure 5.11: Comparisons of the reliability methods for segment S22 (10-mile) for Thursdays, 2003
Figure 5.12: Comparisons of the reliability methods for segment S41 (25-mile) for Thursdays, 2003
CHAPTER 6
COMPUTING TRAVEL TIME RELIABILITY IN TRANSPORTATION NETWORKS WITH MULTI-STATES AND DEPENDENT LINK FAILURES

Abstract

The measurement of transportation network travel time reliability is imperative to provide drivers with accurate route guidance information and to generate the shortest path (or alternative paths) connecting the origins and destinations especially under conditions of varying demands and limited capacities. Previous studies assumed that link failures in a road network are statistically independent and that reliability probabilities are perfectly determinable. In real life, these assumptions are dubious, since the failure of a link in one particular area does not necessarily result in the complete failure of the neighboring link, but may lead to deterioration of its performance. This paper presents a new methodology to study the multi-state system reliability analysis of transportation networks for which one cannot formulate an “all or nothing” type of failure criterion and in which dependent link failures are considered. The methodology is presented, using a numerical example, for computing the probability that travel time between an origin and a destination may exceed a
threshold.

Introduction

Reliability engineering has been studied for many years. Its theory has been widely associated with design and management of communication and computer networks and the performance of mechanical equipment (Kececioglu 1991 and Wolstenholme 1999). In this context, reliability is defined as “the probability that components, products or systems will perform their intended functions satisfactorily for a specified length of time under the stated operating conditions”.

Most studies made two main assumptions in order to make the problem of computing probabilistic reliability more tractable. The first assumption was that physical components (or network links) might be in only two states: up or down (operate or fail). However, for road networks, total failure is a rare event and unreliability sources such as frequent incidents, construction work zones, and weather conditions lead to variations in link capacities and/or speeds. The second assumption is one of statistical independence of link failures, which implies that the probability of a link being operational is independent of the states of the other links in the network. In modeling real transportation network, this assumption does not hold due to the events that may cause simultaneous failures of several links. For example, links within the same geographic vicinity are likely to be affected
simultaneously by the same environmental impacts due to natural causes such as rain, a major hurricane or an earthquake. There have been few attempts to address the statistical dependency issue. However, most if not all of these previous efforts were developed in the context of communication networks. As such, there is a need to develop a methodology that will address these shortcomings. Also, this paper tests the transferability of the communication networks’ models to transportation networks.

Li and Silvester (1984) developed an algorithm called “ORDER” to generate the most probable states of the system in a decreasing probabilities order of occurrence to calculate the upper and lower bounds of the communication network reliability. This approximation approach is used to find the reliability measure by only analyzing the most probable states of the communication network instead of enumerating all possible fail states because some of these states may have very small probabilities, and the network rarely operates at these states.

Chiou and Li (1986) developed an algorithm called “ORDER-M” to generate the most probable $M$ states of the system in a descending order of occurrence probabilities to calculate the reliability of communication networks with statistically independent components operating in more than two modes (multi-mode model) corresponding to different capacities of the link. Lam and Li (1986) developed a model called the event-based reliability model (EBRM) to study the reliability of communication networks in which link failures are statistically dependent. This approach identified and modeled the events that cause
communication link failures without using the conditional probabilities techniques.

Le and Li (1989) developed the “cause-based multimode model” (CBMM) taking into account both statistically dependent failures as well as multimode components. The model is based on the concept of causes that can affect the states of the components. The occurrence of cause “i” does not necessarily result in the failure of component “j”, but can lead to component “j” entering one of its degraded modes.

In modeling real transportation networks, travel time reliability modeling has become increasingly important as a key input for the dynamic route guidance system to generate the shortest path (or alternative paths) connecting the trip origins and destinations. Also, the transportation system could rely on current and projected trends in travel time reliability to set funding priorities, compare a number of possible alternatives using simulated data of existing conditions and projecting future scenarios, and provide up-to-date reliable travel time information to the commuting public.

*Travel time reliability* is a challenging subject because there is no single agreed-upon travel time reliability definition. Different researchers have used different definitions of transportation network travel time reliability. For example, Chen and Recker (2000) defined it as the probability that a trip between a given OD pair can be successfully made within a specified interval of time. And, Shaw and Jackson (2003) defined it as the variability between the expected travel time (based on scheduled or average travel time) and the actual
travel time (due to the effects of non-recurrent congestion or fluctuation in demand during recurrent congestion). The main objective of this paper is to present and apply the “cause-based multimode model” (CBMM), to predict transportation networks’ travel time reliability that an origin demand can reach a specified destination under multimodal dependency link failure conditions which have not been considered before in the calculation of transportation networks’ reliability.

Framework for Network Reliability Analysis

This section presents the developed (CBMM) model that takes into account the multi-mode statistically dependent link failures, the notations used, and the system reliability calculations. The transportation network can be viewed as a system with multiple states and each state is defined by the interaction mechanism between supply and demand. The network supply interacts with various external factors, such as incidents, construction work zones, weather conditions and natural/manmade disasters, which can cause degradation of the network performance by reducing its link capacities. In this paper, the term “causes” will be used to refer to these external factors. It is apparent that the values of both capacity and demand cannot be determined with certainty, and hence a particular state of the network is fully described by the modes in which all of its links are operating (Lisinaski and Levitin 2003).
The Cause-Based Multimode (CBMM) Model

The CBMM model is based on the concept of causes that can affect the modes of the links and the model has the following assumptions.

1. The system consists of $N$ links labeled $(l_1, l_2, ..., l_N)$. Each link $l_j$ is assumed to have multiple modes of operation more than just two (operate/fail) labeled $(m_{j,0}, m_{j,1}, m_{j,2}, ..., m_{j,M})$, where the $M$ modes are labeled by order of decreasing probabilities which means that the probability that link $l_j$ will be in mode $m_{j,0}$ is higher than its probability to be in mode $m_{j,i}$ and so forth.

2. There are $i$ causes, denoted $(c_1, c_2, ..., c_i)$ such as incidents and weather conditions. These capacity degrading events are assumed to be independent and occur with known probabilities ($p_i$).

3. Link dependencies are modeled by the fact that a single cause can affect several links, and a given link can be influenced by several causes.

4. The mode of link $l_j$ depends only on those causes that occurred according to the following assumptions:
   - Links are affected only by a cause when it occurs.
   - Links that are not affected by any cause are in the “up mode”.
   - The effect of cause ($i$) on link ($j$), when it occurs, can be quantified independently of the other causes.
Notations

\( Y_i \) Causes that affect link \( l_j = \{ i \} \) is in the influence zone of cause \( c_i \) effects

\( e_{ij} \) Quantification of the effect of cause \( c_i \) on link \( l_j \), given that \( c_i \) occurs,

\( E_{ij} \) Associated random variable that refers to the link modes (for cause \( i \) and link \( j \))

\( x_i \) \[ \begin{cases} 1 & \text{if cause } c_i \text{ occurs} \\ 0 & \text{otherwise} \end{cases} \]

\( X_k \) \( (x_1, x_2, \ldots, x_i) \); for scenario \( k \)

\( p_i \) Probability that cause \( c_i \) occurs

\( E(X) \) A possible outcome network state vector of a specific scenario = \( (e_y | x_i = 1) \)

\( q_{ij}(x) \) The causes’ effects probabilities = \( \Pr(E_{ij} | x_i = 1) \)

\( S \) \( S = F[X, E(X)] \), The Cause-space Representation of the system (C-R) which is all-possible states in the network as a result of all scenarios.

Calculation of Network Reliability

The system reliability measure is calculated as follows (Le and Li 1989 and Chiou and Li 1986):

\[
R(\Omega) = \sum_{S_h \in \Omega} \Pr(S_h) R(S_h)
\]

Where:

\( S_h \) A system state

\( \Omega \) Set of all possible system states
Pr($S_h$) Probability of state $S_h$

$R(S_h)$ Reliability measure, given that the system is in state $S_h$

An exact calculation of this reliability measure is impractical due to the large number of network states corresponding to the network links being in different modes. Therefore, an approximation method has to be used to calculate the reliability of only the $m$ most probable states (Chiou and Li 1986):

$$R(\Omega') = \sum_{S_h \in \Omega'} \text{Pr}\{S_h\} R\{S_h\}$$

The approximation method proceeds in three steps: (1) generate the set of the most probable $m$ states, (2) determine the corresponding Cause-space Representation (C-R) of the system $S = F[X, E(X)]$, and (3) compute the approximation reliability as shown in Equation 2. The Fault Tree Analysis (FTA) decreasing algorithm will be used to enumerate the $m$ most probable states and to analyze the performance of these states (Hoyland and Rausand 1994).

Most studies in estimating the reliability of a transportation network made two major assumptions: the first assumption is that links are assumed to be in random discrete modes (fail/operate). However, for road networks, total failure is a rare event and the unavoidable unreliability sources (i.e. incidents, construction work zones, and weather conditions) lead to variations in link capacities and/or free-run speeds. The second assumption is one of statistical independence of link failures, which implies that the probability of a link being
operational is independent of the states of the other links in the network. In modeling real transportation network, this assumption does not hold due to the events that may cause simultaneous failures of several links. For example, links within the same geographic vicinity are likely to be affected simultaneously by the same environmental impacts due to natural causes such as a major hurricane or an earthquake. As such, there is a need to develop a methodology that will address these shortcomings.

The main objective of this paper is to present, modify and apply the modified “cause-based multimode model” (CBMM), which developed by Le and Li (1989) to predict transportation networks travel time reliability. This modified model takes into account the multi-mode statistically dependent link failures that have not been considered before in the calculation of transportation networks reliability.

**Fault Tree Analysis**

The Fault Tree Analysis (FTA) is a graphical logical representation of the major faults or critical failures associated with a product that are used for reliability, maintainability and safety analysis (Robert et al. 1990). A fault tree illustrates the probable states of the system’s components and follows a top-down structure (root-leaf). The tree diagram ($T_{AB}$) in Figure 6.1 is divided into two subtrees $T_A$ and $T_B$. The subtree ($T_A$) is used to enumerate and identify the scenarios. It is defined as the top portion of the $T_{AB}$ tree with a height $K$ that
represents the number of independent causes in the network (length of the longest path from a root to a leaf). Given a scenario X (T_A subtree leaf), the subtree denoted as T_B is used in the enumeration and the identification of the network states with a height equals ($\sum_{\nu=1}^{i} |e_{\nu}|$) that represents the number of links in the influence zone of Cause “i”.

**Numerical Example**

The hypothetical network in Figure 6.2 has five nodes, six links, and three traffic zones. The links are labeled 1 through 6 and the free flow travel times are assumed (10 minutes) for simplicity. In the peak period, there are four link-paths from origin (A) to destinations (B and C) as follows: **Path I**: A – Link 1 – Link 3 - B, **Path II**: A – Link 2 – Link 6 - B, **Path III**: A – Link 1 – Link 5 - C, and **Path IV**: A - Link 2 - Link 4 - C. Each link in the network is assumed to have various degraded modes based on the level of congestion (represented by the V/C ratio). Theses modes are assumed as follows: moderate congestion (mode 0 or up mode), heavy congestion (mode 1 or degraded mode), and severe congestion (mode 2 or jam mode) with (V/C) ratios 0.9, 1.2, and 1.5 respectively. The associated random variable ($E_{ij}$) will take one of three values (0, 1 and 2) based on the link mode. Three causes of unreliability and their probabilities of occurrence have been assumed as follows:

- **Cause 1**: rainy weather on **Links 5 and 6**, this will be assumed to affect the upstream Links 1 and 2.
• Cause 2: incident on **Link 3** that will be assumed to affect the upstream Link 1, and Links 2 and 6 that connect Zone (A) with Zone (B).

• Cause 3: incident under rainy weather on **Link 4** and will be assumed to affect all links between Zone (A) and Zone (C) which are Links 1, 2 and 5.

The causes’ effects probabilities on the links \( q_{ij}(z) \) are assumed and listed in Table 6.1, in which \( z \) refers to the link mode (0, 1, or 2). For example, we got \( q_{34}(z) = (0.0, 0.10, 0.90) \) for Cause 3 affecting Link 4 which indicates that \( q_{34}(0) = 0.0 \), \( q_{34}(1) = 0.10 \), and \( q_{34}(2) = 0.90 \), i.e., the occurrence of “Cause 3” means that the probability of Link 4 being in “mode 0” is 0.0 with V/C ratio equals 0.90, the probability of being in “mode 1” is 0.10 with (V/C) ratio equals 1.2, and the probability of being in “mode 2” is 0.90 with (V/C) ratio equals to 1.5.

**Scenarios Enumerations**

To create the subtree \((T_A)\) in Figure 6.1, draw a box at the top of the Fault Tree diagram (Node 0). As a non-leaf (root node), it has two leaves or two children (1 and 2). The connected branches between the nodes are zero or one in which “one” refers to the occurrence of cause \((C_i)\) and “zero” indicates that cause \((C_i)\) does not occur. Similarly, node 1 has two children (3 and 4) and so forth. This procedure is repeated as many times as the subtree height. The height is the number of independent causes \((k = i = 3)\). The leaves of the subtree \((T_A)\) represent possible scenarios. There are \((2^k)\) possible scenarios which resulted in 8 scenarios. The scenarios’ probabilities can be calculated based on that all causes are
assumed to be independent and occur with known probabilities \( p_i \). For example, if only an incident occurs on Link 3 (Cause 2). Then, its corresponding scenario is \((0, 1, 0)\) with 0.03 probability of occurrence. The probability of both an incident (Cause 2) and rainy weather conditions (Cause 1) occurs at the same time, scenario \((1, 1, 0)\), is the product of the two independent events probabilities \((0.03 \times 0.07 = 0.0021)\). The probability of the base scenario \((0, 0, 0)\) can be calculated as follows:

\[
1 - \sum_{i=2}^{4} p_i = 1 - \left[ (0.07 + 0.03 + \ldots + 0.0003) \right] = 0.7656
\]

Then, the cumulative scenarios’ probabilities can be calculated as shown in Table 6.2. For example, both the base and the three independent causes scenarios cumulatively covered about (98.56%) of the network states.

**States Enumerations**

Once the subtree \(T_A\) is created, each scenario \(X\) will have as many leaves as the number of the link operation modes. This process creates the subtree \(T_B\). In this paper, we assumed that each link in the network described in Figure 6.2 could operate in one of three modes as explained earlier. Accordingly, except the base scenario \([X = (0, 0, 0)]\), each scenario has three branches representing each mode as shown in Figure 6.1. The base scenario represents the existing normal conditions “no causes occur”.

Each non-leaf in the subtree \(T_B\) has three branches (0, 1, and 2) and this will be repeated as many times as the subtree height. This height equals to the maximum number of links
affected by the cause. Consequently, each leaf of the subtree $T_B$ represents a system state in the Cause-space Representation of the system (C-R). For example; $T_B[(0, 0, 0)]$ is an empty subtree (base scenario $X_1$) as shown in Figure 6.1, $T_B[(0, 0, 1)]$ is rooted at $T_A$ leaf (scenario $X_2$) in which only Cause 3 occurs, with a possible outcome network state:

$$E\left[\left(X\right)\right] = \{e_j | x_i = 1\} = E\left[(0, 0, 1)\right] = \{e_j | x_j = 1\} = \{e_j\}$$

The above term $(e_{3j})$ is used to refer only to the links that are in the influence zone of Cause “i”. In this case, links (1, 2, 4 & 5) are in the influence zone of Cause 3, therefore $e_{3j} = \{e_{31}, e_{32}, e_{34}, e_{35}\}$ and its height $= \sum x_i | e_j = 4$, see Table 6.1. This means that, under $X_2$ scenario, Cause 3 affects only four links out of the six links in the network in Figure 6.2 and the other two links will operate in the up mode. A particular outcome of $X_2$ scenario could be for example state 1 as shown in Table 6.3 in which the associated random variable has these values $(E_{31} = 1, E_{32} = 1, E_{33} = 0, E_{34} = 2, E_{35} = 1, E_{36} = 0)$. This indicates that Links 1, 2 and 5 have high congestion level $(V/C = 1.2)$. While, Link 4 is in the severe congestion mode $(V/C = 1.5)$. The other links operate in the up mode with $(V/C = 0.9)$ or have moderate congestion. Accordingly, the Cause-space Representations (C-R) of state 1 under scenario $X_2$ can be written as follows:

$$S = F\left[X, E\left(X\right)\right] = F\left[(0, 0, 1), E\left[1, 1, 0, 2, 1, 0\right]\right]$$
**System Travel Time Reliability Measure**

The public is interested in the probability that a network can process traffic within acceptable delay for a given node-to-node traffic demand requirements. Link travel time reliability is defined as the probability $R(T)$ that the expected travel time $E(T_j)$ at degraded capacity is less than the link free flow travel time plus an acceptable threshold $(\Delta)$. The value of $(\Delta)$ is the level of tolerance that the public is willing to accept for link travel time under degraded capacity conditions. In this paper, we will assume that the expected link travel time will be considered at least 95% reliable as long as its value is less than or equal to an upper bound $\{E(T_j) \leq (t_j + \Delta)\}$. For each state of the network (characterized by a set of link modes), the travel time reliability can be calculated as described in the following subsections.

**Travel time Expectation**

In this paper, the Bureau of Public Roads (BPR) formula is used for link performance (Chen et al. 2003):

$$T_j(v_j, C_j) = t_j \left[ 1 + b \left( \frac{v_j}{C_j} \right)^a \right]$$  \hspace{1cm} (3)

Where $t_j$ and $T_j$ are link $j$’s free-flow travel time (which is a deterministic parameter) and the travel time with flow $v_j$ respectively; $b$ and $a$ are constants; $v_j$, $C_j$ and $T_j$ are random
variables. In general, the link travel time will form a probability distribution; its mean or expectation can be determined as:

\[ E(T_j) = t_j + bt_j E\left(\frac{v_j}{C_j}\right)^a \]  \hspace{1cm} (4)

**Link Travel Time Reliability Measure**

Travel time reliability \( R(T) \) can be expressed using the well-defined reliability engineering functions (failure rate or hazard rate function “\( \lambda(T) \)”). Mathematically, the relationship between the reliability and the failure rate (hazard) function can be written as in (Kececioglu 1991, Tobias and Trindade 1995, Hoyland and Rausand 1994, and Wolstenholme 1999):

\[ R(T) = e^{-\int_0^T \lambda(T) dT} \]  \hspace{1cm} (5)

Where: \( \lambda(T) = \frac{f(T)}{R(T)} \) and \( \lambda(T) \) is the probability distribution function. The above equation is called the *generalized reliability function* and is valid for all travel time functions. Once the travel time distribution of a link is known, then the reliability function of that link can be determined. For example, if the travel times of a link are well represented by Weibull distribution, then using Equation 5 yields a general reliability function as follows:

\[ R(T_i) = e^{-\left(\frac{T_i - \gamma}{\eta}\right)^\beta} \]  \hspace{1cm} (6)
Where

$(\beta) \rightarrow$ Shape parameter, $(1 < \beta < 2.6)$, this range causes the Weibull distribution to be positively skewed. For higher values (2.6 to 3.7) the coefficient of skewness approaches zero such that it could approximate the normal distribution. The Weibull distribution will be negatively skewed for values greater than 3.7.

$(\gamma) \rightarrow$ Location parameter, $(\gamma = t_j = \text{Free Flow Travel Time})$, the location parameter is that value of the variable at which the distribution starts and to the left of which $f(T) = 0$. We assume that the minimum link travel time is equal to its travel time at free flow travel time. It is realistic to assume that the curve starts at that value where the probability that the travel time being less than the free flow travel time is very small or equal to zero.

$(\eta) \rightarrow$ Scale parameter, it can be calculated as a function of the acceptable upper limit of travel time $(\tau_i = t_j + \Delta)$ and the corresponding reliability.

Substituting the free flow travel time for $\gamma$ in the above general equation, Equation 6 can be re-written as follows:

$$
\left[-\ln \left( R(T_i) \right) \right]^{\frac{1}{\beta}} = \left( \frac{T_i - t_j}{\eta} \right)
$$

Consequently,

$$
T_1 = t_j + \eta \left[-\ln \left( R(T_i) \right) \right]^{\frac{1}{\beta}}
$$

(7)
Substitute for \( (t_i = t_j + \Delta) \) and consider that \( R(T_i) \) is at least 95% in Equation 7 (see assumption on page 8), thus:

\[
(t_j + \Delta) = t_j + \eta \left[ -\ln \left( 0.95 \right) \right]^{\frac{1}{\beta}}
\]

Then, Substitute for \( \beta = 2.17 \) to minimize the Weibull mean, because it is known that the mean of the Weibull distribution is given as \( \left[ \bar{Y} = \gamma + \eta \Gamma \left( \frac{1}{\beta} \right) + 1 \right] \), where \( \Gamma \left( \frac{1}{\beta} + 1 \right) \) is the Gamma function. The minimum Gamma function is obtained at \( \beta = 2.17 \) (Kececioglu 1991). The scale parameter can be obtained as follows:

\[
\eta = \frac{\Delta}{\left[ -\ln(0.95) \right]^{\frac{1}{\beta}}} = \left( \frac{\Delta}{0.2544} \right)
\]

(8)

**Network Travel Time Reliability Measure**

The transportation network configuration of the links and how they are arranged (in series, in parallel, or as a combination of both) must be first determined to compute the system reliability. Calculating the reliabilities for the individual series and parallel sections and then combining them in the appropriate manner is the proper way of analyzing such systems. This methodology is illustrated in the following example. Consider a system with three links. Links A and B are connected in series and link C is connected in parallel with the first two. An approach for estimating the reliability is to define the successful paths for this system.
$E_1 = AB$ and $E_2 = C$. The reliability of the system is simply the probability of the union of these paths:

$$R_S = P(E_1 \cup E_2) = P(AB) + P(C) - P(ABC) = R_A R_B + R_C - R_A R_B R_C$$  \hspace{1cm} (9)$$

Generally, for the successful multi-path network system we can manipulate Equation (9) to estimate reliability as:

$$R_S = 1 - \prod_{j=1}^{W} (1 - R_{Path,j}) = 1 - \prod_{j=1}^{W} (1 - R_{Path,j}) \hspace{1cm} (10)$$

Where $J$ is the path label and $W$ is the number of possible parallel paths in the transportation network.

**Travel Time Reliability Numerical Example**

We now apply the **CBMM** model to the reliability analysis of an example network as shown in Figure 6.2. In this paper, the link travel time function used is the BPR standard function with $b = 0.15$ and $a = 4$ as mentioned in (Chen et al. 2003). Also, we assume that travel time is acceptable up to the point when demand reaches capacity. This means that the acceptable extra time above the free flow travel time will occur at the capacity level (demand = capacity). Hence, the acceptable travel time threshold ($\Delta$) will be 15% of the free flow travel time. This is because $b$ in the BPR function = 0.15. For the above reason, the upper travel time threshold will be the free flow travel time plus the acceptable time or 115% of the free flow travel time.
Consequently, the scale parameter of the Weibull distribution with \( \beta = 2.17 \) can be calculated using Equation 8:

\[
\eta = \left( \frac{\Delta}{0.2544} \right) = \left( \frac{0.15 \cdot t_i}{0.2544} \right) = 0.5896 \cdot t_i
\]

**Network Travel Time Reliability**

In constructing network reliability, enumeration of all possible network states is impractical because the number of network states grows exponentially. For example, there are \( M^N \) states for the network in our example (Figure 6.2), where \( N \) is the number of links and \( M \) is the number of possible modes for each link. The Fault Tree Analysis Algorithm (FTA) is used to generate the network states \( Q \) which begins with the base state “no causes occur or normal conditions exist” with (0.7656) probability of occurrence. The developed \( Q \) states are arranged in decreasing order based on the values of the network states probabilities as shown in Table 6.3. For example, state 5 is a particular outcome of Scenario \((1, 0, 0)\) where it rains on Links 5 and 6 with a network state **Cause-space Representation**:

\[
S = F[X, E(X)] = F[(1, 0, 0), E(0, 1, 0, 0, 1, 1)]
\]

Its probability equals to the scenario probability of occurrence (i.e., rainy weather = 0.07) times the probability of each link being in described earlier modes (0, 1, or 2) simultaneously as listed in Table 6.1. In this case, the probability of the network being in state 5 can be calculated as follows: 

\[
[0.07 \times (0.8 \times 0.6 \times 1.0 \times 1.0 \times 0.6 \times 0.6) = 0.0121]
\]
Table 6.3 shows the network scenarios, the corresponding states vector (possible permutations of functional modes of all system links) arranged in decreasing order based on the states’ probabilities. The system’s coverage in Table 6.3 represents the cumulative probability of the network states’ probabilities. For example, the sum of the first ten states plus the base state has a cumulative coverage value 0.8868 which represents about 88.68% of the entire network states and so forth. The state vectors are used to estimate the \((V/C)\) ratios based on the assumptions explained earlier on page 171, in which \((V/C)\) ratios were (0.9, 1.2, and 1.5) for modes 0, 1, and 2 respectively. A shaded cell in Table 6.3 means that the link demand exceeds capacity \((V/C)\) is greater than 1.0).

As mentioned earlier, it is impractical to calculate the exact network reliability due to the large number of network states and most of them rarely occur. Therefore, an approximation method has to be used to calculate the reliability of only the \(m\) most probable states. These \(m\) states will be identified as long as the cumulative probability of the arranged decreasing order \(Q\) network states exceeds the desired coverage which is assumed 0.95. The results in Table 6.3 confirm that the \(m\) most probable states are 31 with an actual coverage (0.9508), which is greater than the desired coverage. These 31 most probable states covered more than 95% of the overall network states and represented the level of confidence in the analysis with only less than 5.0% of the network states that rarely occur would not be considered. For each state of the 31 most probable network states, we calculate the travel time of each link using the BPR standard formula. For example, to calculate the travel time reliability of Link 5
with free flow travel time \((t_i = 10\) minutes) in state 5 explained above which has a state vector \((0, 1, 0, 0, 1, 1)\). The state vector indicates that Link 5 is operating in the degraded mode or \((V/C)\) ratio equals 1.2 as shown in Table 6.3. As a result, Link 5 travel time equals to \((10 \times (1 + 1.15 \times 1.20)^4 = 13.11\) min\). Obviously, the estimated travel time is greater than the upper threshold \((10 \times 1.15 = 11.5\) min\).

Thus, the calculated reliability is expected to be less than 95\% because the percentage of travel time above the free flow travel time is higher than \((\Delta = 15\%)\). The link travel time reliability is calculated as:

\[
R(T_i) = e^{-\left(\frac{T_i - t_i}{\eta}\right)^\mu} = e^{-\left(\frac{13.11 - 10}{0.5896 \times 10}\right)^{2.17}} = 77.91\%
\]

The path travel time reliability is calculated based on the reliability formula for the series configuration. For example, to calculate the travel time reliability of Path I: A-Link 1-Link 3-B, we multiply the reliabilities of Link 1 and Link 3 as follows:

\[
R_{Path_I} = \prod_{i=1}^{N=2} (R_i) = (R_{Link1} \times R_{Link3})
\]

There are two paths connected in parallel for each pair of zones, so the system reliabilities are calculated using Equation 10. The links and paths travel time reliabilities are shown in Table 6.3. A straight average of the 31 most probable states is simple, but it would not be accurate because the occurrence probability of each state is different. Therefore, the
weighted average is used to account for the proportional relevance of each state, rather than treating each state equally, see Table 6.6. As expected, Link 4 and Path IV had the lowest weighted average reliability values, 88.75% and 84.68% respectively, due to the existing of incident under rainy weather on Link 4 with the highest probability of occurrence among the three causes (0.12).

Figure 6.3 shows the path and network travel time reliability corresponding to the 31 most probable states. As expected Path I, Path II, Path III, Path IV, and the network as a whole were observed to be reliable under the normal conditions (state 0) in which the demand does not exceed the capacity. In contrast, for the 31 most probable states Path I, Path II, Path III, and Path IV were unreliable for most of the states during the peak period in which the delay between the Origin (A) and the two destinations (B & C) is considered unacceptable due to the series configuration of the paths’ links. However, the system travel time was found to be unreliable for only 13 states out of the 31 most probable states due to the parallel configuration of the two paths for each pair of zones.

The lowest travel time reliability value for the traffic demand movement from Zone (A) to Zone (B) was 31.67% in states 4 and 17, see Table 6.4. These two states occurred under “incident with rainy weather” scenario with state vectors (2, 2, 0, 2, 1, 0) and (2, 2, 0, 2, 0, 0) and had 0.013 and 0.003 probabilities of occurrence respectively, see Table 6.3. Similarly, from Zone (A) to Zone (C), the lowest travel time reliability values were 16.49%, 19.93%
and 25.68% in states 4, 17 and 3 which are scenarios of the incident under rainy weather with
0.013, 0.003 and 0.013 probabilities as shown in Table 6.3 and Table 6.4.

Therefore, by knowing the system state it should be possible to provide the commuting
public with travel time reliability information and generate the most reliable path (or
alternative paths) connecting trip origins and destinations. Furthermore, by calculating the
path travel time reliability for each of the \( m \) most probable states \( R\{S_h\} \) and estimating the
probability of each state \( Pr\{S_h\} \) as shown in Table 6.3, it will be possible to compute the path
and network lower and upper travel time reliabilities by using Equation 2.

We can get a lower reliability, if we considered only the 31 most probable states and ignored
all other states \( (R\{S_h\} = 0) \) and we can get an upper reliability if we considered all other
states \( (R\{S_h\} = 1.0) \) but the 31 most probable states as shown in Table 6.4. For example, the
lowest of the lower values can be calculated by considering only the base state (state 0) and
ignoring all other states, and the highest of the upper values can be calculated by considering
all states but the base state (state 0). For Path I, the lowest of the lower values will equal to
the multiplication of the base state probability and its reliability value \( (76.56 \times 95.97 + 2.16 \times
0 + \ldots = 73.48\%) \). While the highest of the upper values is obtained as follows: \( 1 - 76.56 \times (1 -
95.97) = 96.92\% \) as shown in Table 6.4. As long as one of the states is included then the
multiplication of its probability and reliability values is added to the previous calculated lower value to compute the new lower amount or the multiplication of its probability and unreliability, where unreliability = 1 – reliability, is subtracted from the previous upper value as shown in Table 6.4.

The reliability lower and upper values were plotted as a function of the most probable states (figure is not shown here due to space limitations). There was a convergence between the upper and lower curves as the number of network states considered increased. The most representative value with 95% confidence can be obtained by considering the most 31 probable states, which covered 95.08% of the network states. For example, Path I travel time reliability for the 31 most probable states had a lower value of 85.7% and an upper value equal to 90.7%. This means that Path I is at least as reliable as the lower obtained value. In other words, the probability that the network satisfies the external traffic demands on Path I (i.e., Path I travel time delay between zone (A) and zone (B) is within the acceptable limit), is at least 85.7% using these (m=31) states. Also, Path II, Path III, and Path IV travel time reliabilities were at least 82.9%, 84.5% and 80.5% respectively during the peak period as shown in Table 6.4.

As expected, Path IV had the smallest lower and upper values and Path I had the highest lower and upper values. This is because along Path IV, Cause 3 (incident under rainy weather with 0.12 probability) occurred on Link 4, and Link 2 is affected by the three
capacity degradation causes. Along **Path 1**, Cause 2 (incident with 0.03 probability) occurred on Link 3, and Link 1 is affected by the three causes. It can be concluded that the impact of the cause probability of occurrence ($p_i$) is significant and affects the degradation on the path and the entire network reliability.

The system network travel time reliability lower and upper values were 91.9% and 96.8% for the movement from Zone (A) to Zone (B) and 89.7% and 94.7% for the movement from Zone (A) to Zone (C). These reliability bounds are greater than the corresponding values for the individual paths connecting between these two pairs of zones due to the parallel configuration of the two paths. This gives drivers the opportunity to divert among these paths.

**Comparison between Independency and Dependency Assumptions**

In Table 6.1 under the dependency link failure assumption, the occurrence of “Cause 3” affected Links 1, 2, 4, and 5. The combinations of state vectors for all possible link modes were shown in Table 6.3. For the independency link failure assumption, the occurrence of “Cause 3” will only affect Link 4. The other three Links (1, 2, and 5) will be assumed to operate in the up mode (mode 0). Accordingly, the highlighted cells in Table 6.1 show only the links that will be affected by the three causes of capacity degradation under independency assumption. The dependency analysis procedure including the tables and figures are
repeated under the independency assumptions. Due to word limit, only a sample of the independency tables will be presented in this paper. Table 6.5 demonstrates that there are 13 most probable states which covered at least 98.56% of the entire network states compared to 95.08% of the 31 most probable states under the dependency assumption. The main question is: Which assumption leads to more accurate results?

On the surface, the independency assumption would seem to have less number of states and covers more percentage of the entire network state therefore it is more attractive. However, the results of this assumption suffer from lack of accuracy. For example, Path II’s lower and upper travel time reliabilities were 82.9% and 87.8% under the dependency assumption and these values became 92.7% and 94.1% under the independency assumptions as shown in Tables 6.4 and 6.5. Similarly, the network reliability lower and upper bounds for the movement from Zone (A) to Zone (C) increased from 89.7% and 94.7% under the dependency assumption to 98.0% and 99.4% under the independency assumptions. Consequently, the dependency assumption indicated that the network delay between zones (A) and (C) is considered unacceptable 10.3% of the time during the peak period and compared to only 2.0% under the independency assumption. Due to this significant difference between the results of the two assumptions, traffic managers would prefer the more conservative approach, namely the dependency assumption, because it is more accurate and on the safe side.
The results of the two assumptions are compared in Table 6.6. Links 1 and 2 weighted average reliabilities are 98.0% under the independency assumption compared to 93.3% and 90.9% under the dependency assumption. Also, the two links had travel time reliability value as low as 17.7% in more than one state compared to 98.0% reliability under the independency assumption. On the zonal level, there is a large difference in the minimum travel time reliability with 96.7% under independency assumption compared to 31.7% under dependency assumption for the movement from zone (A) to zone (B), and 16.5% for the movement between Zone (A) to Zone (C). Finally, it is expected that the independency assumption will have more negative effects on travel time reliability calculations in more complex networks, but this remains to be demonstrated in a future paper.

**Conclusions**

Network travel time reliability is a subject of great practical importance to planners and engineers involved in network design. The reliability of travel time measure can be used as a tool to provide travelers with accurate information about the most reliable paths connecting origins and destinations. This paper developed and applied a new methodology to estimate the travel time reliability of a transportation network and its paths during the peak period in which links can degrade in a multimode, statistically dependent manner. This method has not been used before in modeling the reliability of transportation networks.
Travel time reliability has been computed for the system’s most probable states. The Fault Tree Analysis (FTA) algorithm was used to enumerate the most \( m \) probable states in decreasing order of probability. Then, the cause-based multimodal model (CBMM) was used to estimate travel time reliability of the network, which was defined as the probability that the traffic demand is satisfied. By knowing the system states, this new method estimates lower and upper bounds of reliabilities for network paths and for the entire network.

The analysis showed that the dependency assumption is important to obtain accurate travel time reliability of links, paths, and the entire network. For example, the minimum network travel time reliability under the link dependency assumption was 16.49\% for one of the possible states compared to 96.67\% under the independency assumption. This large discrepancy will shake the public’s confidence in the transportation systems and those who manage them. Daily commuters are under continuous stress of the unknown. Realistic scenarios which consider the dependency assumption provide more accurate information that aid travelers in making better choices. Inaccurate information caused by the independency assumption could add to the travelers’ anxiety associated with the unknown length of delay. This always reflects negatively on highway agencies and management of taxpayers’ resources.

Only a small size network has been tested in this paper. The developed method has true potential and can be easily extended to large-scale networks as long as the data is available to
estimate and predict travel time reliability in real time, or assess the historical performance of transportation networks. Future research will focus on extending this methodology to real life networks to develop the best-fit distributions for travel time reliability so there will be no need to assume the distribution parameters. Also, it will focus on traveler surveys to determine the travelers’ perception of travel time reliability and acceptable thresholds of delay above free flow travel time. Finally, the new method will be extended further to accommodate variations in the O-D demand table.

References


Table 6.1: The causes’ effects link probabilities ($q_y(z)$)

<table>
<thead>
<tr>
<th>Cause</th>
<th>Rainy Weather (0.07)</th>
<th>Incident (0.03)</th>
<th>Incident under Rain (0.12)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Up</td>
<td>Degraded</td>
<td>Jam</td>
</tr>
<tr>
<td>Link1</td>
<td>0.80</td>
<td>0.20</td>
<td>0.00</td>
</tr>
<tr>
<td>Link2</td>
<td>0.40</td>
<td>0.60</td>
<td>0.00</td>
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<tr>
<td>Link3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Link4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Link5</td>
<td>0.20</td>
<td>0.60</td>
<td>0.20</td>
</tr>
<tr>
<td>Link6</td>
<td>0.20</td>
<td>0.60</td>
<td>0.20</td>
</tr>
</tbody>
</table>

— A blank entry means that Cause “i” has no effect on Link “j”.
— Highlighted cells show the locations of Cause “i” occurrence.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Probability</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0, 0, 0)</td>
<td>0.7656</td>
<td>0.7656</td>
</tr>
<tr>
<td>(1, 0, 0)</td>
<td>0.0700</td>
<td>0.8356</td>
</tr>
<tr>
<td>(0, 1, 0)</td>
<td>0.0300</td>
<td>0.8656</td>
</tr>
<tr>
<td>(0, 0, 1)</td>
<td>0.1200</td>
<td>0.9856</td>
</tr>
<tr>
<td>(1, 1, 0)</td>
<td>0.0021</td>
<td>0.9877</td>
</tr>
<tr>
<td>(1, 0, 1)</td>
<td>0.0084</td>
<td>0.9961</td>
</tr>
<tr>
<td>(0, 1, 1)</td>
<td>0.0036</td>
<td>0.9997</td>
</tr>
<tr>
<td>(1, 1, 1)</td>
<td>0.0003</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
Table 6.3: Network most probable states vectors and the corresponding link (V/C) ratios

<table>
<thead>
<tr>
<th>State</th>
<th>Scenario</th>
<th>State Vector</th>
<th>Probability</th>
<th>Coverage</th>
<th>Path I</th>
<th>Path II</th>
<th>Path III</th>
<th>Path IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>(0, 0, 0)</td>
<td>(0 0 0 0 0)</td>
<td>0.7656</td>
<td>97.97%</td>
<td>97.97%</td>
<td>97.97%</td>
<td>97.97%</td>
<td>95.97%</td>
</tr>
<tr>
<td>1</td>
<td>(0, 1)</td>
<td>(1 1 0 2 1)</td>
<td>0.0216</td>
<td>77.91%</td>
<td>77.91%</td>
<td>77.91%</td>
<td>77.91%</td>
<td>76.32%</td>
</tr>
<tr>
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- The highlighted cells show the links with (V/C) ratio greater than 1.0
Table 6.4: The most probable states travel time reliabilities

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$P = $ State probability, $R = $ State reliability, $LR = $ Lower reliability, and $UB = $ Upper reliability

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Table 6.5: The most probable states travel time reliability bounds under independency link failure assumption

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<td>(0 0 0 0 2)</td>
<td>0.28</td>
<td>96.0</td>
<td>0.3</td>
<td>92.1</td>
<td>94.0</td>
<td>1.7</td>
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<td>0.28</td>
<td>96.0</td>
<td>0.3</td>
<td>92.3</td>
<td>94.0</td>
<td>1.7</td>
<td>99.9</td>
</tr>
<tr>
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<td>(0 0 0 2 2)</td>
<td>0.28</td>
<td>96.0</td>
<td>0.3</td>
<td>92.6</td>
<td>94.0</td>
<td>1.7</td>
<td>99.9</td>
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Table 6.6: Summary comparison between the dependency and independency assumptions

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<th>Descriptive Statistics</th>
<th>Dependency</th>
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<th></th>
<th></th>
<th>Indepedency</th>
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<tr>
<td></td>
<td>Mean</td>
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<td>Min</td>
<td>Median</td>
<td>Mean</td>
<td>Weighted Average</td>
<td>Min</td>
<td>Median</td>
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<td>Min</td>
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<td>98.0%</td>
<td>98.0%</td>
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<td>98.0%</td>
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<td>98.0%</td>
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<tr>
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<td>91.7%</td>
<td>95.9%</td>
<td>17.7%</td>
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<td>77.5%</td>
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<td>17.3%</td>
<td>96.0%</td>
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<td>98.0%</td>
<td>98.0%</td>
</tr>
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<td>3.1%</td>
<td>76.3%</td>
<td>89.8%</td>
<td>87.1%</td>
<td>17.3%</td>
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<tr>
<td>System (AB)</td>
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<td>96.6%</td>
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<td>99.7%</td>
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<td>99.4%</td>
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<tr>
<td>System (AC)</td>
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<td>94.4%</td>
<td>16.5%</td>
<td>94.4%</td>
<td>98.8%</td>
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<td>99.4%</td>
<td>98.0%</td>
<td>98.0%</td>
<td>98.0%</td>
</tr>
</tbody>
</table>
Leaves of the subtree = (C-R)

Network state

Scenario (X)

T_A

Node of the tree

Branch of the tree (cause occurrence)

0

T_B

Empty subtree

Branch of the tree (link mode)

Node 0: Root node and parent of nodes 1 & 2

Nodes 1, 2: Children of node 0

State 1: [(0, 0, 1), {(1, 1, 0, 1, 0, 0)}]

State 5: [(1, 0, 0), {(0, 1, 0, 1, 1)}]

Leaves of the subtree = (C-R)

Network state

Non-leaf nodes of the subtree

Figure 6.1: Graphical presentation of the Fault Tree Analysis, see numerical example
Figure 6.2: Study network in numerical example
Figure 6.3: Estimate of the path/network travel time reliabilities
CHAPTER 7
CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH

New measures of system performance and quality are crucial to operation and management of our existing facilities. Transportation network reliability is a relatively new performance measure and is a subject of great practical importance to planners and engineers involved in network design. Transportation systems could rely on current and projected trends in the reliability measure to assess transportation deficiencies and potential improvements, to set funding or programming priorities by comparing between competing alternatives, and to provide up-to-date reliable travel time information to the commuting public based on current or historical databases.

A new method for estimating reliability was developed and applied to a hypothetical network to estimate network travel time and capacity reliability measures under non-recurring congestion conditions with degraded link capacities. Both measures demonstrated similar performance and have the potential of being useful for estimating the reliability of a road network. However, travel time reliability is more interesting and easier to understand by the public. It can be used as a tool to provide travelers with accurate information about the most reliable paths connecting origins and destinations.
In this dissertation, travel time reliability is defined in a way that is totally different from the existing methods. Unlike the existing methods (Florida and Buffer Time) which define travel time reliability in terms of travel time variability, the definition of reliability in the new method places more emphasis on the traveler’s perspective. In this dissertation, segment travel time reliability is defined as the probability that the expected travel time is less than the segment travel time at posted speed limit. In other words, if segment travel time is less than or equal to travel time at posted speed limit, then this segment is considered 100% reliable. Otherwise, the developed reliability stochastic models will be used to calculate the segment/corridor travel time reliability for a specific departure time. The new method is more sensitive to the traveler’s perspective since it reflects that an increase in the segment’s travel time should always result in less travel time reliability. By doing this we assume that the public will be 100% satisfied if traffic conditions allow them to travel at the roadway facility speed limit.

Applying the new method to the I-4 corridor in Orlando, Florida followed this initial theoretical effort and basic research. This dissertation utilized a real life transportation data warehouse to estimate travel time reliability of the I-4 corridor, four different stochastic models were tested: Weibull, Exponential, Lognormal, and Normal. Two evaluation criteria were used in selecting the best-fit model: 1) *Anderson-Darling* (AD) Goodness of Fit statistic, and 2) Error percentages. Based on these criteria, the Lognormal stochastic model provided the best fit of travel time reliability for the evening peak period of the I-4 corridor.
(eastbound). Also, this dissertation examined the impact of data sample composition on the estimation of the distribution parameters. Accordingly, it was more efficient to use the same day of the week (e.g., Mondays) in the estimation of travel time reliability for I-4 segments than using mixed data (i.e., first week of the month) because of the significant differences between the weekdays within the same week. The developed Lognormal model was used to estimate segment and corridor travel time reliabilities. The vulnerability of the existing methods, especially when applied to congested freeway segments with high travel time variability, was demonstrated using real life data. These common methods were insensitive to the traveler’s perspective of travel time on the I-4 congested segments.

Furthermore, the new method showed high sensitivity to the geographical location that reflects the level of congestion and bottlenecks. A major advantage of the new method over the existing ones is its strong potential in the ability to estimate travel time reliability as a function of departure time. The new method is more appropriate for freeway operations because it treats travel time as a continuous variable that captures the variability experienced by individual travelers over an extended period of time.

This dissertation also examined the impact of the segment length in miles on the accuracy of travel time reliability estimation of the freeway corridor. The developed travel time reliability models showed significant evidence of the relationship between the segment
length and the results’ accuracy. The longer the segment, the less accurate were the travel
time reliability estimates. As a result, long segments (e.g., 25 miles) are more appropriate for
planning purposes as a macroscopic performance measure of the freeway corridor. Short
segments (e.g., 5 miles) are more appropriate for the evaluation of freeway operations as a
microscopic performance measure.

The new method did not ignore the traveler, it sat an expectation for the level of travel
quality for the traveler (customer). Thresholds assumed in this study need to be verified
through comprehensive traveler behavior surveys. It is strongly recommended to conduct a
national survey to determine the public’s satisfaction with travel time reliability. Also, more
accurate assessment of reliability levels matched with travel time thresholds could be
determined based on such surveys. When survey results are known, thresholds assumed in
this study can be replaced with more realistic ones. The basic steps of this methodology still
apply with real life data albeit using different thresholds. This emphasizes the flexibility of
the new method.

The newly developed method has a strong potential of being used to compute and predict
travel time reliability of the freeway corridor in real time, assess the historical performance
of freeway corridors. Also, segment travel time reliability can be used as a tool to provide
travelers and freight companies with accurate information about the corridor congestion level
to help in planning and scheduling their trips.
Further, this dissertation has explored the impact of relaxing an important assumption in reliability analysis: Link independency. In real life, assuming that link failures in a road network are statistically independent is dubious. Since the failure of a link in one particular area does not necessarily result in the complete failure of the neighboring link, but may lead to deterioration of its performance. The “Cause-Based Multimode Model” (CBMM) has been used to address link dependency in communication networks. However, the transferability of this model to transportation networks has not been tested and this approach has not been considered before in the calculation of transportation networks’ reliability. This dissertation presented the CBMM and applied it to predict transportation networks’ travel time reliability that an origin demand can reach a specified destination under multimodal dependency link failure conditions.

Travel time reliability was computed for the system’s most probable states. The Fault Tree Analysis (FTA) algorithm was used to enumerate the most $m$ probable states in decreasing order of probability. Then, the Cause-Based Multimodal Model (CBMM) was used to estimate travel time reliability of the network, which was defined as the probability that the traffic demand is satisfied. By knowing the system states, this new method estimates lower and upper bounds of reliabilities for network paths and for the entire network. The developed method has true potential and can be extended to large-scale networks as long as the data is available to estimate and predict travel time reliability in real time, or assess the historical performance of transportation networks.
The results showed that the dependency assumption is important to obtain accurate travel time reliability of links, paths, and the entire network. The large discrepancy in the minimum network travel time reliability between the link dependency and independency assumptions will shake the public’s confidence in the transportation systems and those who manage them. Daily commuters are under continuous stress of the unknown. Realistic scenarios which consider the dependency assumption provide more accurate information that aid travelers in making better choices. In contrast, deceptive information caused by the independency assumption could add to the travelers’ anxiety associated with the unknown length of delay. This normally reflects negatively on highway agencies and management of taxpayers’ resources.

Future research can focus on traveler surveys in an effort to determine the travelers’ perception of travel time reliability and acceptable thresholds of delay above travel time at speed limit. Using the I-4 data warehouse, this new methodology can be tested for peak and off peak periods (e.g., morning and midday) and weekends for different segment lengths of 5, 10, and 20 miles. The new method has the true potential to be extended to compute reliability for large-scale real life networks including: other freeways with similar surveillance data, toll roads with Electronic Toll Collection (ETC) and probe vehicles’ travel time data extracted from Automatic Vehicle Identification (AVI) records, and surface streets data from probe vehicles equipped with AVI.
The methodology used in this study can be used in the derivation of a customer Level of Service (LOS), and the determination of the most reliable weekday and departure time for making trips. Finally, the impact of quantifying travel time reliability on user equilibrium under various travel choices can be tested in the future. More specifically, future research can focus on investigating the most appropriate method to disseminate travel time reliability information to the public as pre-trip or en-route information so travelers can make improved travel decisions. For the dependency analysis, future research can focus on extending the developed methodology (CBMM) to real life networks as long as the data is available. Also, this methodology can be extended further to accommodate variations in the O-D demand table.