TOWARD SMART MOBILITY BY ENHANCING TRAVEL-TIME RELIABILITY

A Thesis
IN
Computer Science

Presented to the Faculty of the University
of Missouri–Kansas City in partial fulfillment of
the requirements for the degree

MASTER OF SCIENCE

by
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TOWARD SMART MOBILITY BY ENHANCING TRAVEL-TIME RELIABILITY

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University of Missouri–Kansas City, 2018

ABSTRACT

Here is my abstract – Smart mobility is an essential element in building smart cities. To realize connected and automated smart mobility as a service, the capability to efficiently estimate the travel-time reliability measures responding to various operating conditions is of critical importance. My research topic mostly focuses on a travel-time reliability estimation system, which is applied to determine the effects of the operational changes on the travel-time reliability. The application results to the metro freeway network in Minnesota indicate the substantial improvements in travel-time reliability after the changes were introduced, indicating the possibility of modeling the causal relationship between reliability and specific operational strategies.

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the School of Computing and Engineering, have examined a thesis titled "Toward smart Mobility by Enhancing Travel-Time Reliability," presented by Avinash Sankarasetty, candidate for the Master of Science degree, and certify that in their opinion it is worthy of acceptance.

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Secondly, I would like to thank University of Missouri-Kansas City for providing me with a platform to plan and execute my research work.

Finally, I would like to thank my parents for their enormous support and spiritual guidance in every walk of life.They are the backbone of all my academic progress to date.

CHAPTER 1

INTRODUCTION

Smart mobility is one of the eight essential aspects that define a Smart City. Developing a reliable roadway network that can provide consistent travel times under various operating conditions is of critical importance in providing efficient, safe and environmentally friendly mobility services [1]. An essential element in developing such smart mobility service systems is the capability to monitor and assess the travel-time reliability of given traffic systems responding to various operating conditions and management strategies. While the importance of travel-time reliability in measuring the performance of the transportation systems has been well recognized by the transportation professionals [2], the current state-of-the-practice in traffic management has not reached the point where various types of reliability measures are automatically generated and incorporated into the daily operations of a given network. To be sure, some studies have estimated the reliability measures affected by external operating conditions, such as work-zones and incidents [3], [4], very few research efforts to identify the causal relationships between reliability measures and specific operational strategies have been found in the literature. The primary difficulty lies with the fact that estimating the travel-time reliability measures requires an extensive process for gathering and managing a significant amount of data from multiple sources, such as traffic, weather, incident, special events and construction databases. Such a complicated process in estimating reliability measures and the lack of the precise knowledge regarding the effects of specific management strategies on the travel-time reliability makes it difficult for practicing engineers to develop and prioritize the reliability-oriented operational methods for a given network.

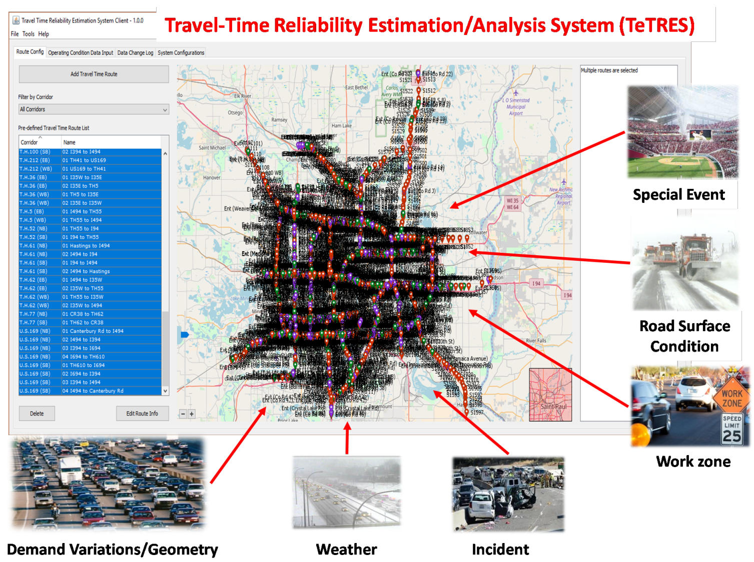

Figure 1: Travel-Time Reliability Estimation System(TeTRES)

My thesis mainly focuses on Travel-Time Reliability Estimation System (TeTRES) and an assessment of the travel-time reliability variations resulting from the recent operational changes in the metro freeway network in Twin Cities, Minnesota. First, as illustrated in Figure 1, a comprehensive data collection and analysis system was developed for efficient estimation of a list of the travel-time reliability indices by integrating various types of data, including traffic flow, weather, incidents, work zones and special events [5]. The resulting TeTRES is then applied to estimate the travel-time reliability measures in the metro freeway corridors before and after two operational changes were implemented, i.e., an adaptive ramp metering [6] and the short-term aggressive incident management during the 2018 Super-Bowl event in Minneapolis, Minnesota [7].

The rest of this paper describes the main features of TeTRES and the field assessment results of the operational changes in the travel-time reliability.

CHAPTER 2

BACKGROUND

Travel-time reliability is formally defined by the US Department of Transportation as the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day [1]. While the quantification of the reliability of traffic systems have been studied by several researchers [8], [9], [10], the most comprehensive effort to date has been made by the Strategic Highway Research Program 2- SHRP2 [11], where a series of the research projects were conducted to organize the existing reliability concepts and develop a set of the practical guidelines in measuring the travel-time reliability for a given network [11], [12], [13]. For example, the SHRP2-L14 project has developed a lexicon summarizing the existing reliability indices and their potential application areas [12]. Further, a process to develop the travel-time reliability monitoring system was developed in SHRP2 L02 [13]. The reliability measures identified from the SHRP2 projects include 90th or 95th percentile travel time, buffer index, planning time index, and frequency that congestion exceeds some expected threshold, travel-time index, semi-variance and misery index. Among them the most commonly used ones are the buffer and planning time indices, whose specific formula are as follows [1], [12], [13]:

$$Buffer\ Index = \frac{(\text{95th \%ile Travel Time} - \text{Average Travel Time})}{\text{Average Travel Time}}$$

$$Planning\ Time\ Index = \frac{\text{95th \%ile Travel Time}}{\text{Free Flow Travel Time}}$$

As shown in the above formula, the buffer index represents the extra buffer time travelers add to their average travel time to arrive on time 95% of all trips, while the planning time index indicates the total travel time reflecting both typical and unexpected delays for a given roadway [11], [12], [13].

CHAPTER 3

TRAVEL-TIME RELIABILITY ESTIMATION SYSTEM ARCHITECTURE

In this section, we present the architecture of TeTRES and estimation of travel-time reliability measures with infrastructure-based sensors.

3.1 Estimation of Travel-Time Reliability Measures with Infrastructure-based Sensors

Figure 2 shows the structure of the Travel-Time Reliability Estimation System (TeTRES) developed at the University of Minnesota Duluth to estimate the travel-time reliability measures, identified in SHRP2, of the freeway corridors in the Twin Citiesâ metro area in Minnesota. As indicated in Figure 2, TeTRES adopts the server-client structure, where all the computational engines, including travel-time calculation/categorization and reliability estimation modules, reside in the server, while the user-clients handle the processes for configuring travel-time routes, specifying the operating conditions to estimate reliability and generating outputs. In particular, most of the data needed for reliability calculation, such as traffic and weather data, can be automatically downloaded following predefined-time schedules. While the current version of TeTRES is designed to work with the existing infrastructure-based sensors, such as loop or radar detectors, in calculating travel times, other types of sensors can be easily accommodated in the current structure. The detailed architecture of TeTRES can be found elsewhere [5].

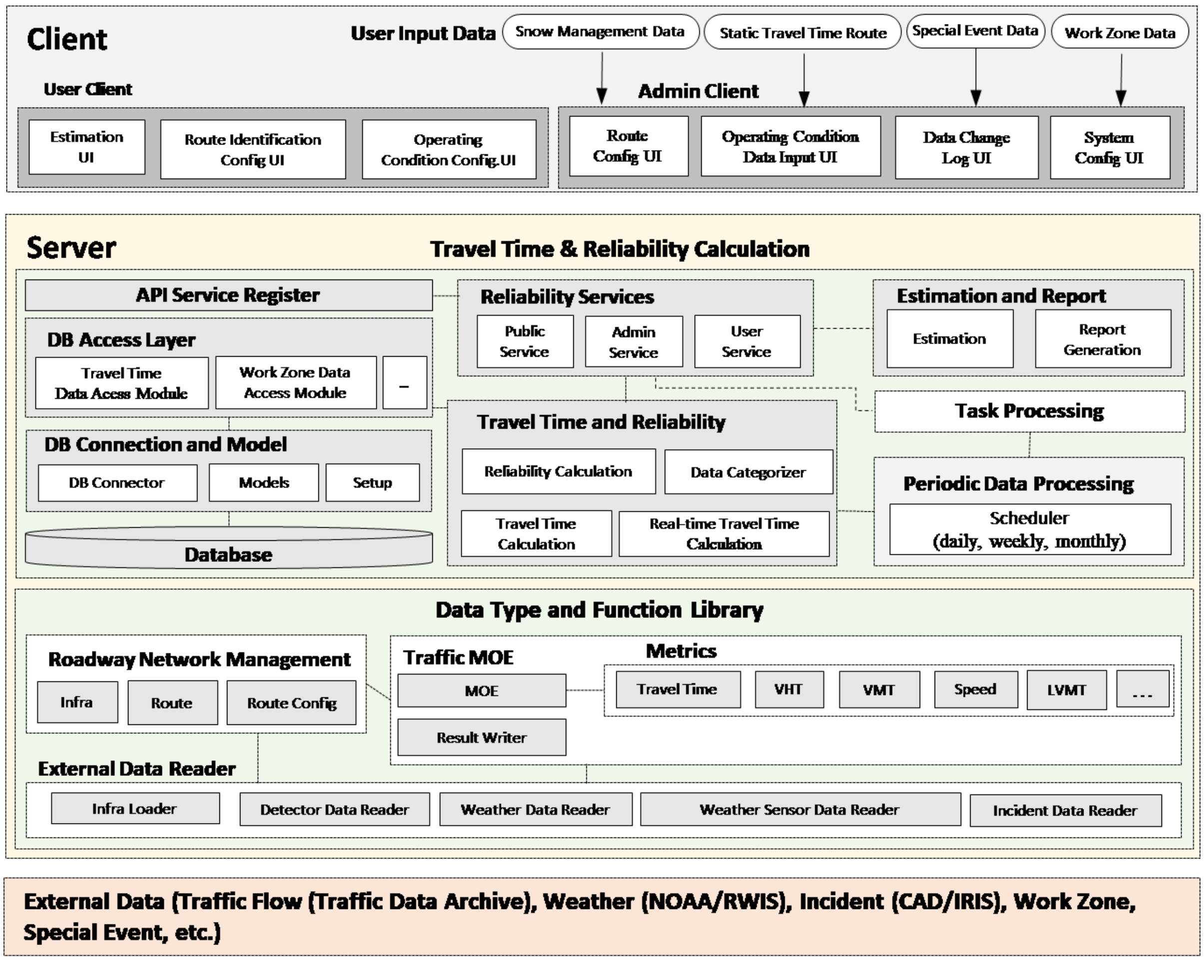

Figure 2: Structure of Travel-Time Reliability Estimation System

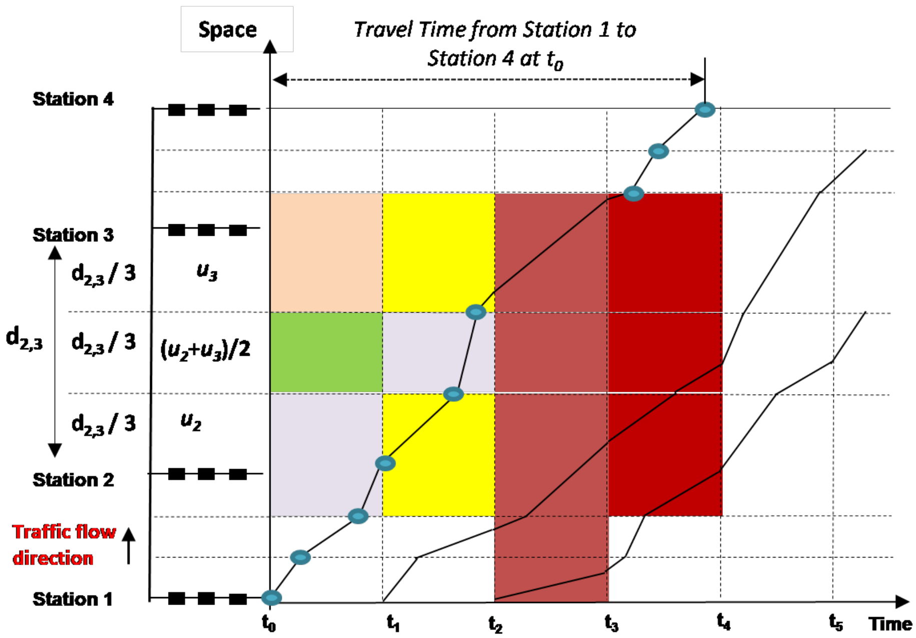

Figure 3: Vehicle Trajectory Identification with the speed Data from Loop Detectors

Figure 3 illustrates the travel-time calculation process using the traffic-speed data collected from the loop-detector stations in a freeway corridor. As shown in Figure 3, the travel-time estimation procedure first divides a section between two detector stations on a given route into three equal-length subsections and determines the speed of each subsection using the measured speed data, ui, from station i for each time interval. The speed values of each subsection for each time interval are then applied to determine the travel-trajectory of a vehicle leaving the first station at the beginning of each time interval until it reaches the last station of a given route. The travel-time is then calculated as the difference between the departure time at the first station and the arrival time at the last station of a given route. In the current TeTRES, the travel time of each user-defined route is calculated every 5 min on a daily basis. The details of the above process and the field test results can be found elsewhere [6]. The travel times of given routes are then categorized by the user-specified operating conditions.

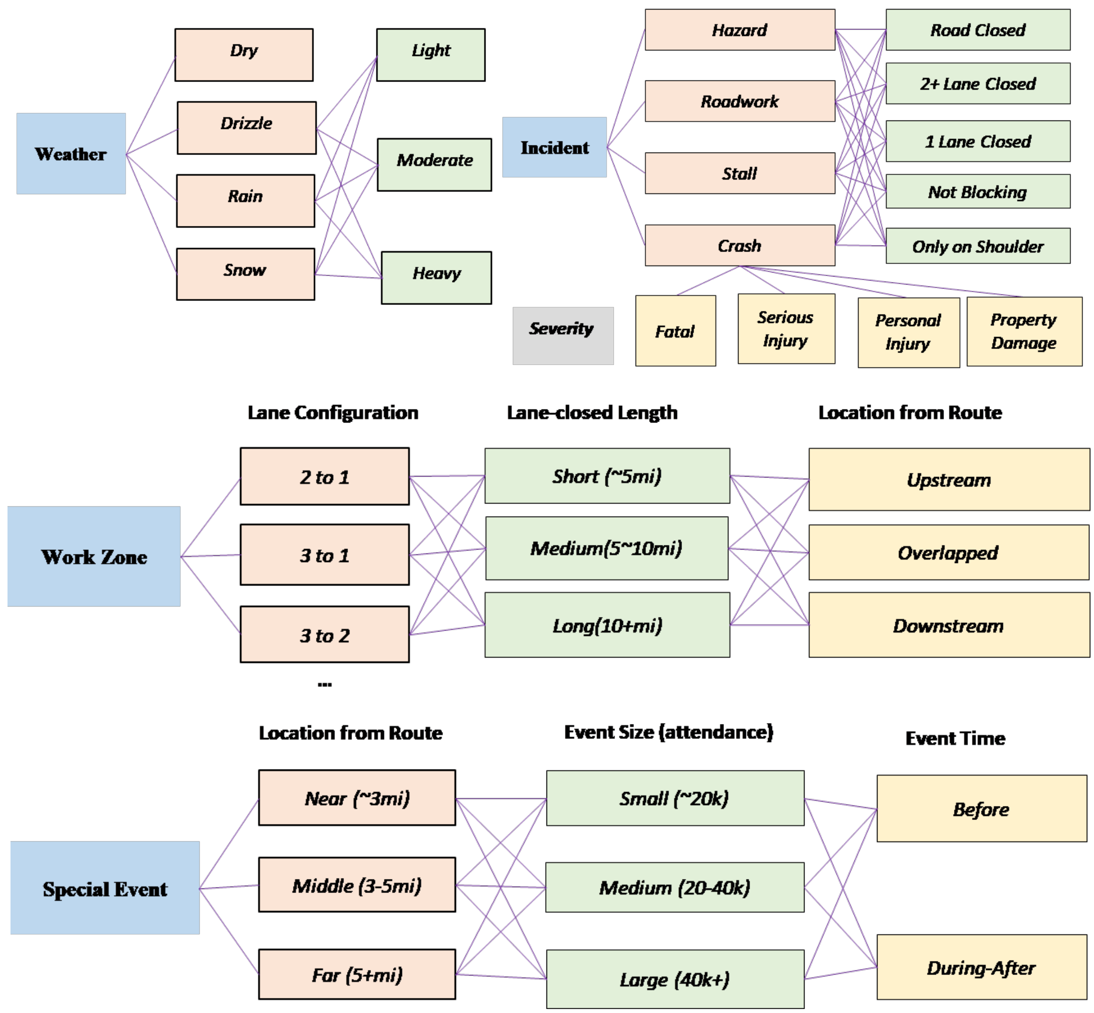

Figure 4: Combination of External Operating Condition affecting Reliability

Figure 4 includes the various types of operating-condition combinations that can be defined in the current version of TeTRES, whose reliability-estimation module calculates the reliability indices for given routes and time periods using only the travel-time data collected under specific operating conditions defined by user. A screen-shot of the user-client for entering specific conditions to estimate reliability measures for the selected routes is illustrated in Figure 5.

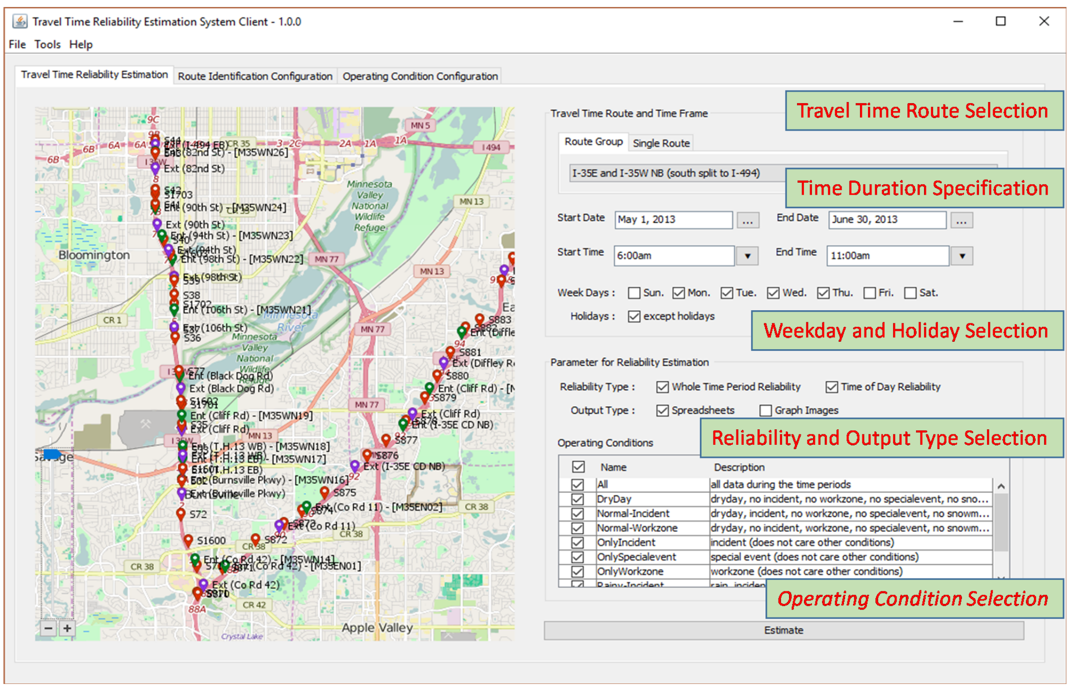

Figure 5: Travel-Time Reliability Estimation Client Panel

3.2 Development of Detailed Design of the Travel Time Reliability System

The main modules of the travel time reliability system are TeTRES server, User Client, and Admin Client. The Server configuration and the non-traffic data are managed by the Admin Client. The users can access the travel time reliability information and obtain the reliability reports by using the User Client program that can be used to configure freeway routes, calculates travel time and estimate the impacts of the external factors on the travel time reliability.The main functions of this modules are as follows:

3.2.1 TeTRES Server

Estimation of travel times and the reliability measures for the predefined Routes. Storage of the estimated information to the database. Provision of the API service to the external services and clients.

3.2.2 Admin Client

Configuration of the variable routes. Calculation of the travel times and reliability indices for both the fixed routes on the server and the user customized routes. Estimation of the impacts of the non-traffic data on the travel time reliability for selected routes.

3.2.3 User Client

Server configuration, lane configuration of work zone and the management of the external data.

3.3 TeTRES Server

TeTRES Server estimates the travel time and the reliability measures based on the historical data and provides the clients with the estimated information through the API services.The components of the server are illustrated in Figure 6. Administrator sets the operational server configuration such as the target freeway routes, job schedule of the estimation process and non-traffic data source information. The non-traffic data are imported manually by the Administrator. All requests from the Admin client are handled by Server Configuration component. The Periodic Job component conducts the periodic estimation process by using the Reliability Engine following the pre-defined schedule by the administrator. User client and external service can access the stored information through the Data API component via HTTP. The rest of this section describes the details of each component.

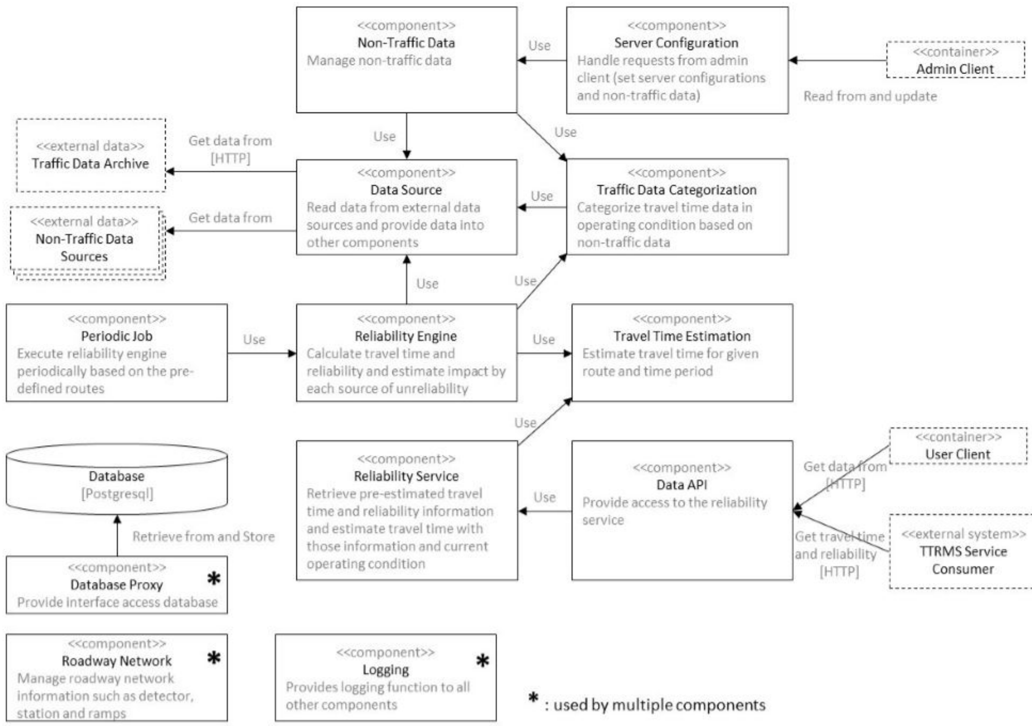

Figure 6: Components of TeTRES Server

3.4 Admin Client

TeTRES Sever also uses the non-traffic data located in the external systems. The location information of these external data sources, such as server IP, port and protocol, is managed by the Admin Client so that the server can collect the data automatically. In addition, the data import function is provided by the Non-Traffic Data Configuration component for manually updating the data. In particular, the user interface for the lane configuration of work zones is provided to correctly configure work-zone lanes, so that the travel times with work zones can be estimated correctly. Figure 7 shows the components of the Admin Client. Roadway Network and Logging components developed at the sever container are reused here. The details of each component are included in the rest of this section.

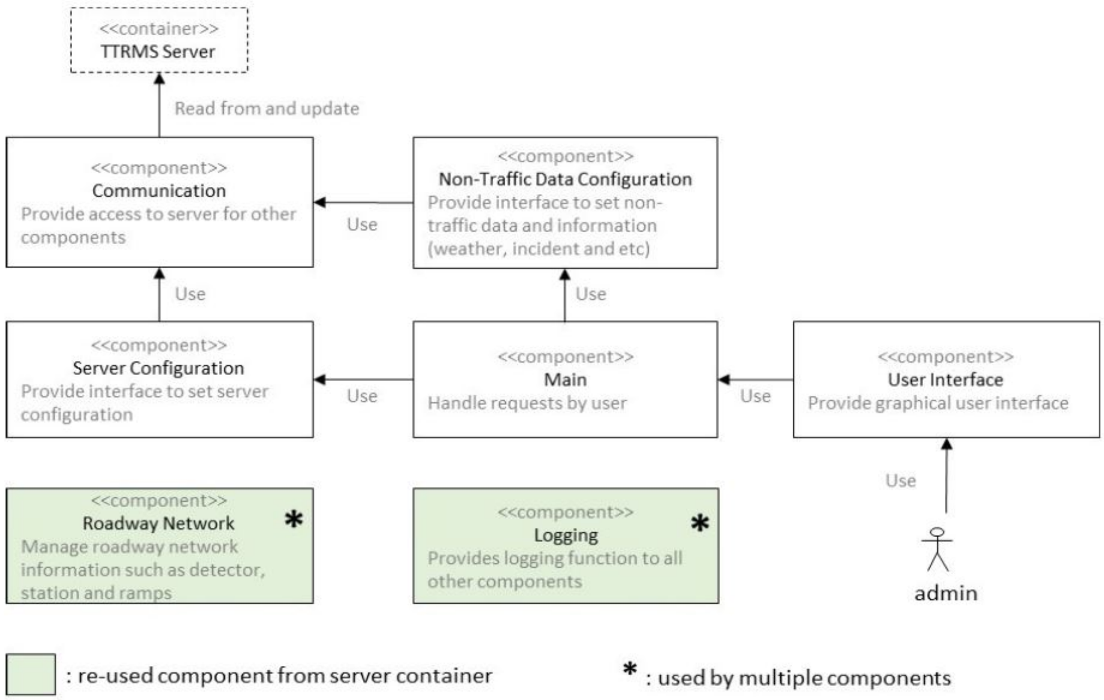

Figure 7: Components of Admin Client

3.5 User Client

User Client retrieves the travel time and reliability information from the server for the fixed routes and generates the reports. The same type of information for the user-defined the variable routes can be also retrieved for the report generation. However, the non-traffic data exists only in the server. The client should use the Data API of the server to access the non-traffic data, while the traffic data are directly accessible via HTTP.

Figure 8 shows the components of the User Client, which also reuses some modules from the server, such as the Reliability Engine, Traffic Data Categorization, Travel Time Estimation, Roadway Network and Logging components, to estimate the travel times and to analyze the impacts of the non-traffic factors on the reliability for both fixed and variable routes. In what follows, the details of each component in the User Client are described.

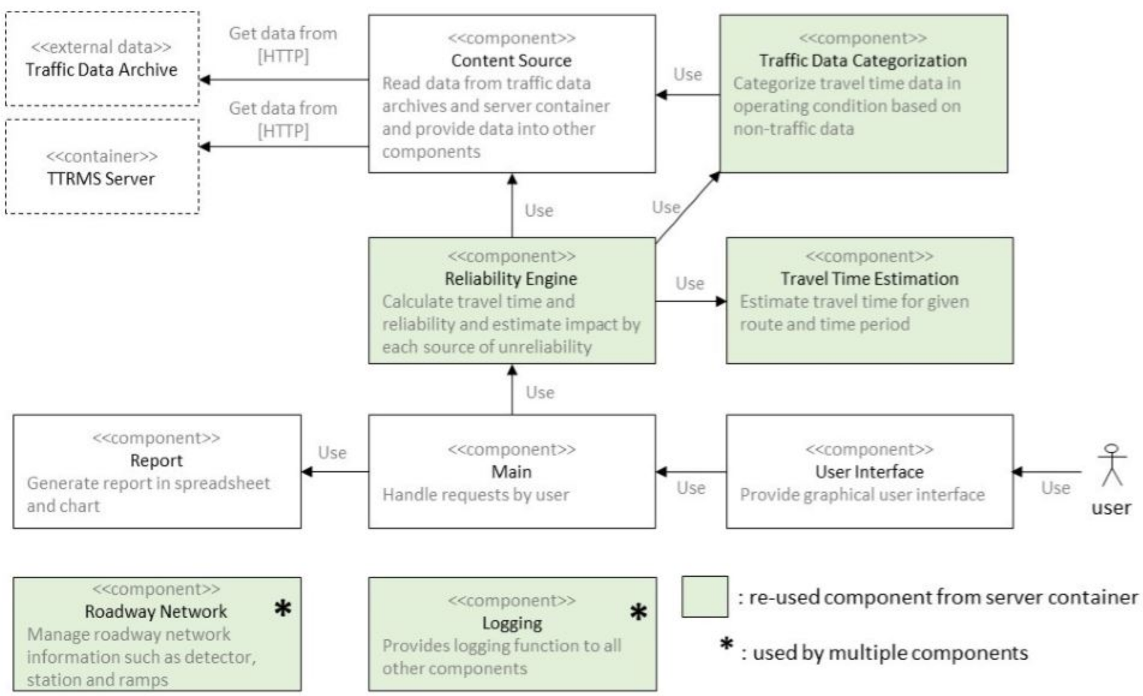

Figure 8: Components of User Client

CHAPTER 4

CASE STUDIES

4.1 Effects of Adaptive Ramp Metering on Reliability in Freeway Corridors

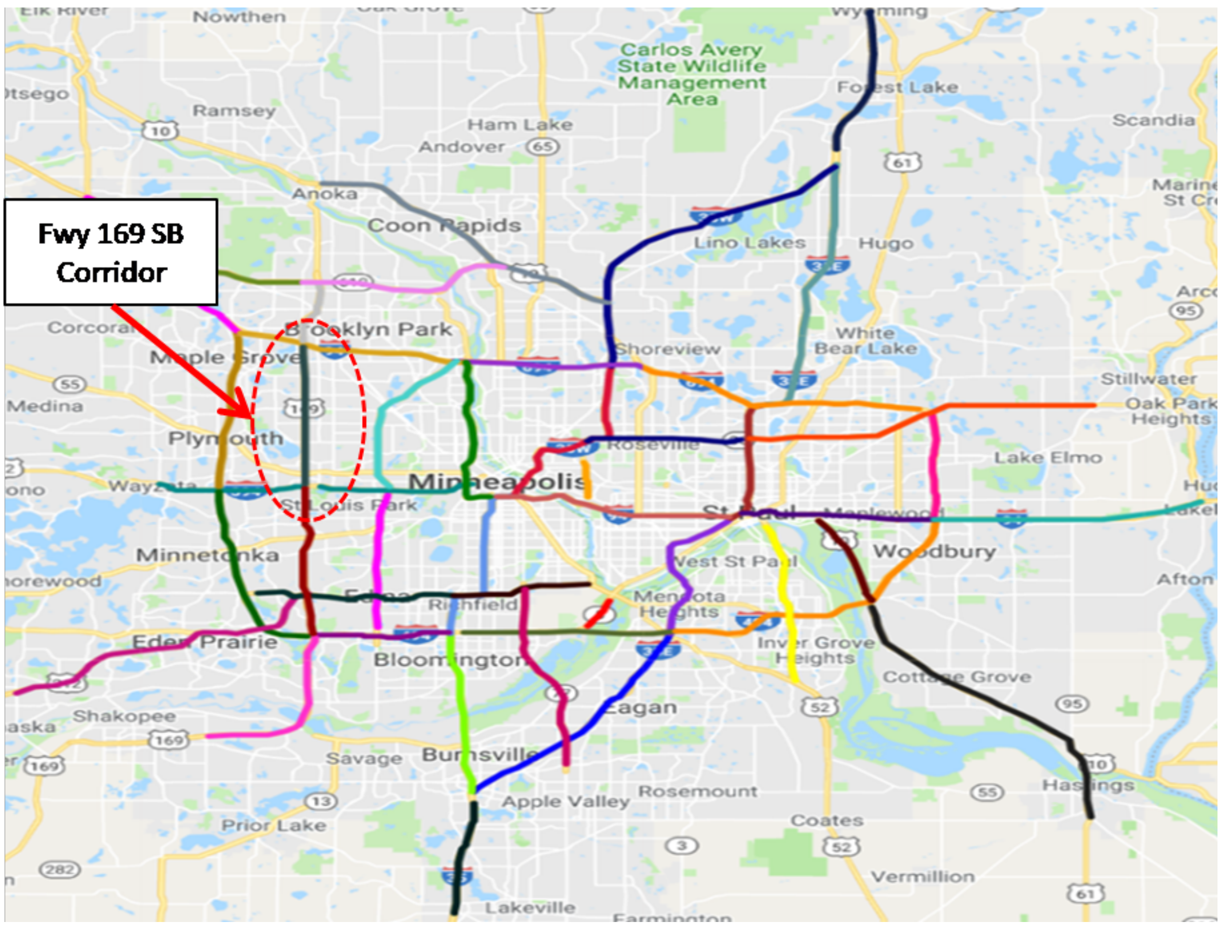

Figure 9: Metro Freeway Network in Twin Cities, Minnesota

Figure 9 shows the location of the 169 southbound corridor in metro freeway network in Twin Cities, Minnesota, where TeTRES has been applied to estimate the effects of the adaptive ramp metering strategy, which was developed at the University of Minnesota Duluth and implemented by the Minnesota Department of Transportation on April 18, 2013 on this corridor. The adaptive metering scheme first identifies the bottlenecks in a given corridor by examining the acceleration/deceleration rates of the traffic flow between two consecutive detector stations using the speed values collected every 30 seconds from each station. Next, for each bottleneck station, a metering zone is defined and the minimum/maximum rates of each entrance ramp within a given zone are determined with the consideration of the operational restrictions, such as the maximum wait time and the on-ramp queue size. Finally, the metering rate of each entrance ramp is calculated with the dynamic control rule, which is based on the density of the mainline segment and also adjusted through time by reflecting the minimum/maximum rates of each ramp. The details of the adaptive metering strategy and its test results can be found elsewhere [6]. For this assessment, the daily values of the planning-time index (PTI-95th %ile) of the 169 southbound corridor during the morning peak period, i.e., 6:00 a.m. to 10:00 a.m., were estimated with TeTRES for each weekday before and after the new metering scheme was activated. Further, to address the effects of traffic demand on the reliability, the daily values of the total vehicle-miles-traveled (VMT) are calculated for the same corridor and time periods. In this analysis, the VMT and PTI values of the normal weekdays under dry weather condition were selected, so that only the effects of the metering changes can be reflected in the resulting reliability estimates. Figure 10 shows the relationships between the daily VMT and planning-time index in the test corridor during the before and after periods in 2013. It can be noted that the after period ends on June 10, 2013, when a new construction started in this corridor. As indicated in Figure 10, the high values of the planning-time index after the new metering strategy was implemented are consistently lower than those in the before period at compatible VMT values. Further, the range of the âafterâ PTI values is substantially narrower than that of the âbeforeâ period, indicating both the severity of congestion and the variability of the travel time were significantly reduced during the morning peak-period in this corridor with the new adaptive metering strategy.

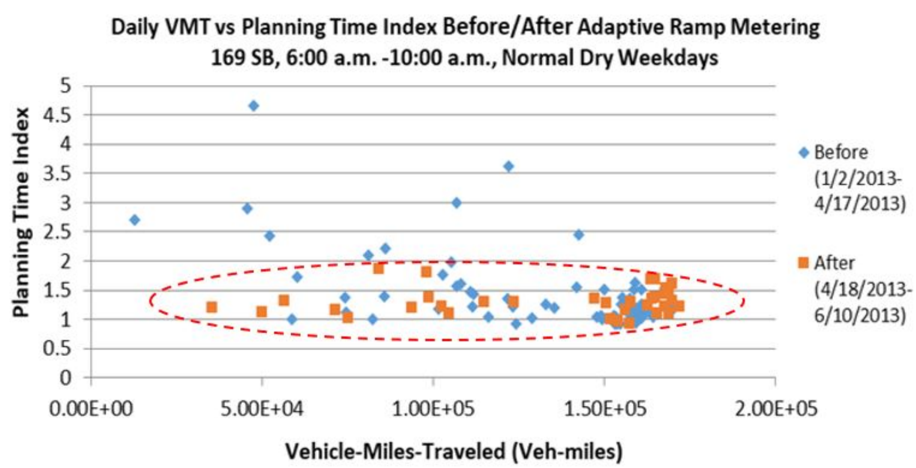

Figure 10: Daily VMT vs Planning Time Index (169 SB)

4.2 Effects of Short-term Aggressive Incident Management during 2018 Super-Bowl Event on Reliability

This section analyzes the effects of the aggressive incident management strategy, conducted during the 2018 Super-Bowl week, i.e., from January 26, 2018 until February 4, 2018, in Minneapolis, Minnesota, on the travel-time reliability in the metro freeway corridors. According to the Regional Traffic Management Center, Minnesota Department of Transportation, the State Patrol leadership instructed their troopers to expedite the clearance of incidents on metro area freeways during the week of the Super Bowl. Troopers were encouraged to only activate rear facing emergency lights so as to not cause gawker slowdowns in the opposing direction. They were also encouraged to relocate non-injury minor crashes as soon as possible to side streets, frontage roads, or parking lots. The above measures were intended to reduce the clearance time of the minor property-damage only incidents and to mitigate the negative impacts on the opposing flows [7].

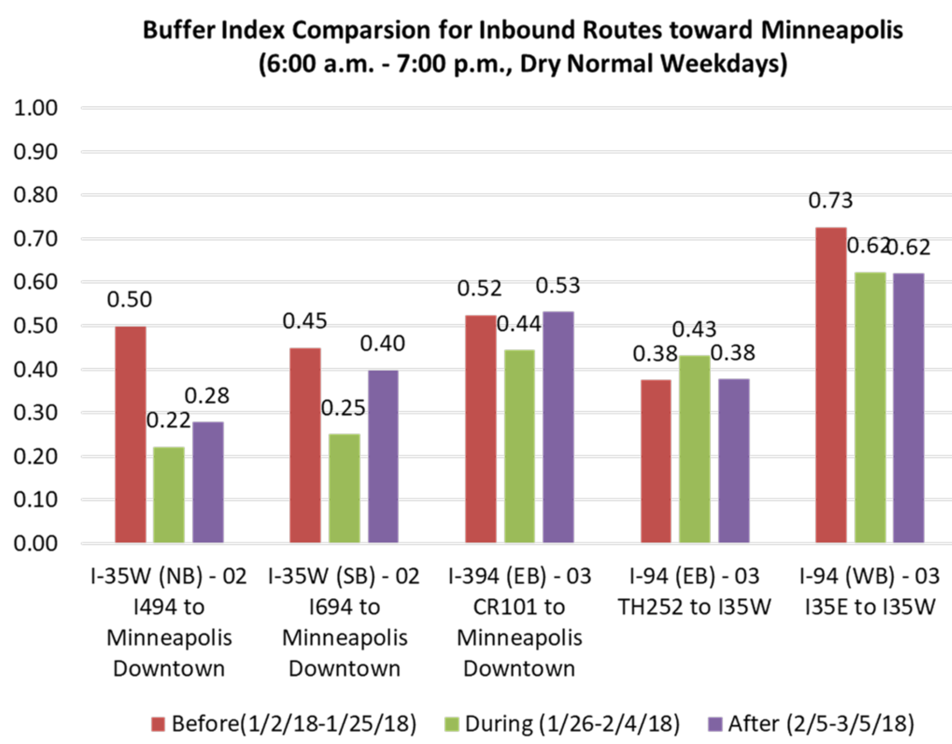

Figure 11: Comparison of Buffer Indices

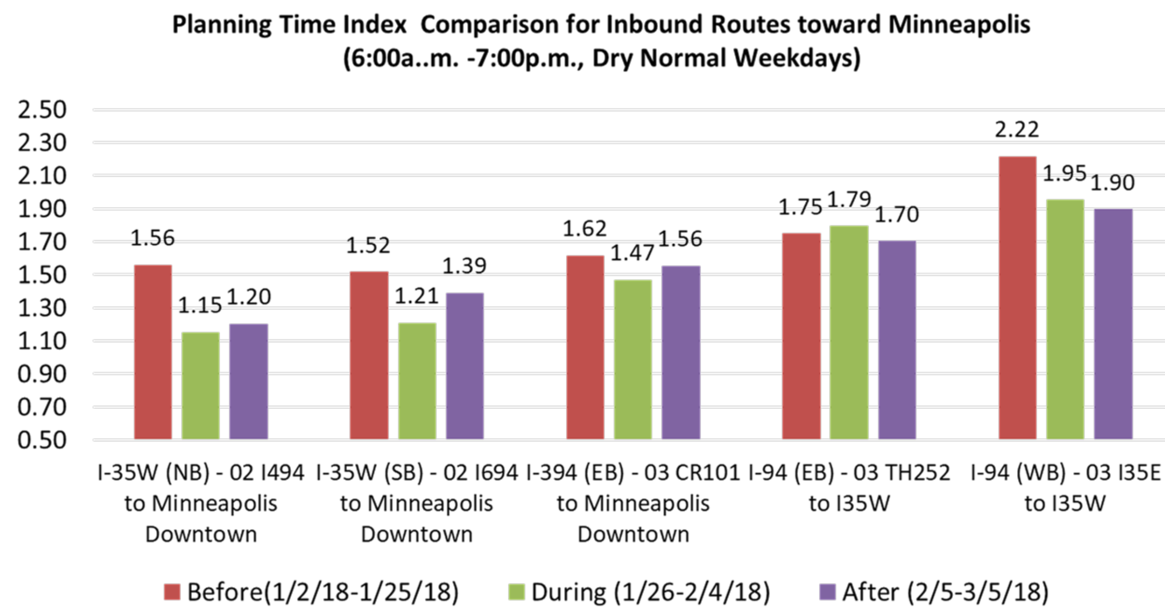

Figure 12: Comparison of Planning Time Indices

The effects of the above incident-management strategy on the travel-time reliability were examined by estimating the reliability indices of the major corridors towards the Minneapolis downtown, where the Super-Bowl venue was located. Specifically, the 95th percentile buffer and planning-time indices of the normal weekdays during the 6:00 a.m.-7:00 p.m. period before, during and after the Super-Bowl week were estimated for the normal weekdays under dry weather condition. Figures 11 and 12 show the values of the buffer and planning-time indices of the five major routes coming towards the Minneapolis downtown on the normal weekdays. As indicated in these figures, both buffer and planning-time indices of the four routes show consistently reduced values during the Super-Bowl period compared to those during the before and after periods, while no significant differences were observed in one route.

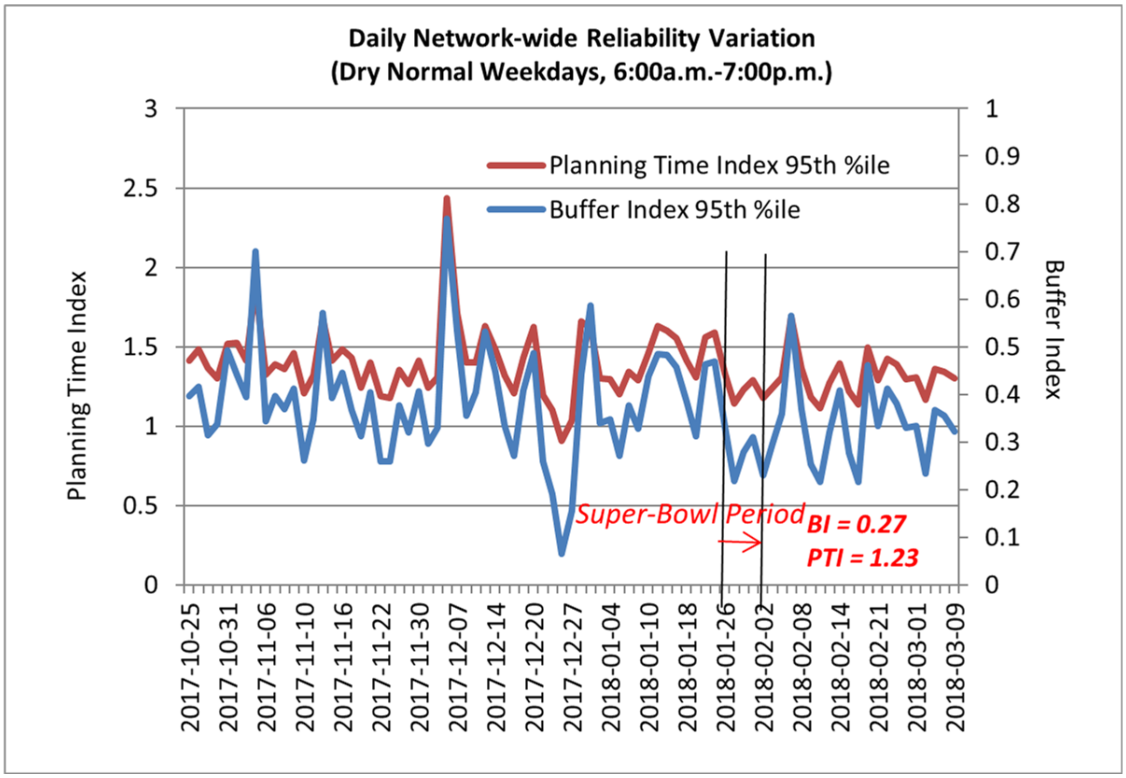

Figure 13: Comparison of Planning Time Indices

Figure 13 shows the daily variations of the network-wide buffer and planning-time indices during the same time periods. The network-wide indices are the weighted averages of the buffer and planning-time indices of all the individual routes in the metro network. The VMT of each route was used as the weight. As indicated in Figure 10, the network-wide indices during the Super-Bowl event clearly show reduced values compared to those during before and after periods. The above results appear to indicate the short-term aggressive incident management scheme made a positive impact on the travel-time reliability in the metro freeway network.

4.3 Comparing The Travel Times Using TeTRES and Google Maps

We are having the past real time calculated data for all the defined routes using travel time estimation system. So now we will compare the real travel times data in TeTRES system with the Google maps travel time. So the Figure 15 shows the huge variation of real time travel times data when compared with the Google. Google maps having the estimated time which is constant and same all the time for different years as well. So for this I have defined a Network in Travel Time reliability estimation system which consists of three possible routes from starting to ending point.For the same Google shows three possible routes which are indicated as G1, G2, and G3 as shown in Figure 14. The variations that are occurred in TeTRES results are due to the Work zone, Incident, Weather, Special Events, and snow Managements. From the graphs we can observe that the Google travel time are showing fixed travel times which may not be useful for the future prediction and whereas TeTRES have real travel times which can be useful for the estimation for travel times.

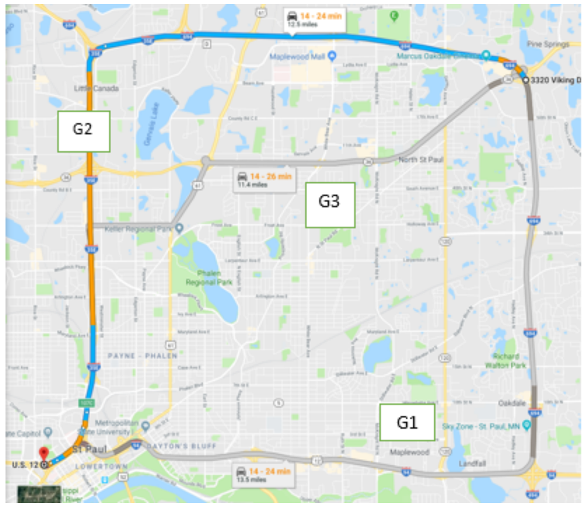

Figure 14: Google map possible Routes from start to end

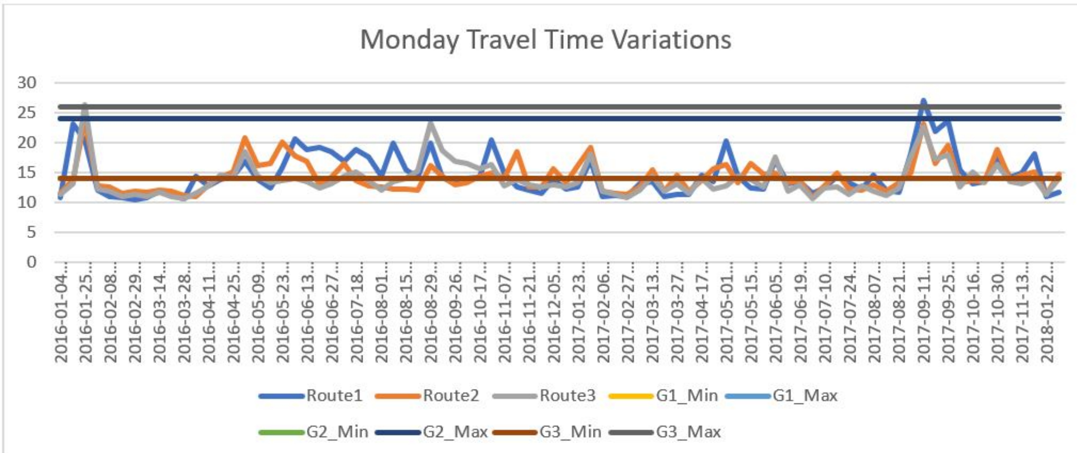

Figure 15: Monday Travel Time Variation

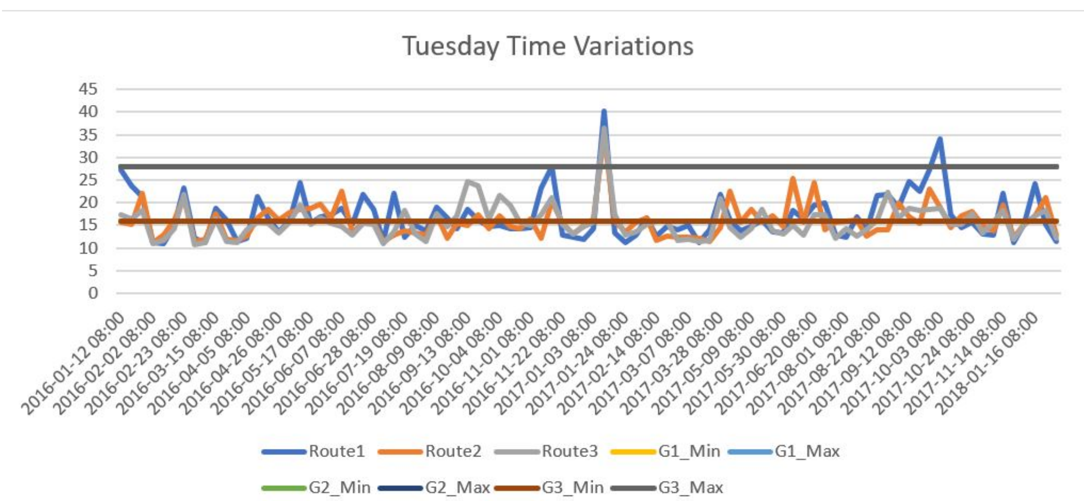

Figure 16: Tuesday Travel Time Variation

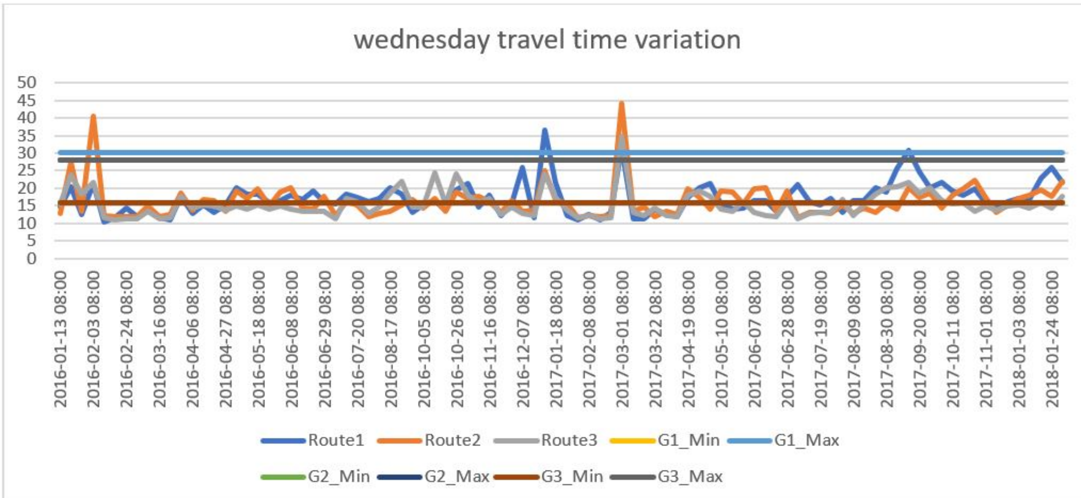

Figure 17: Wednesday Travel Time Variation

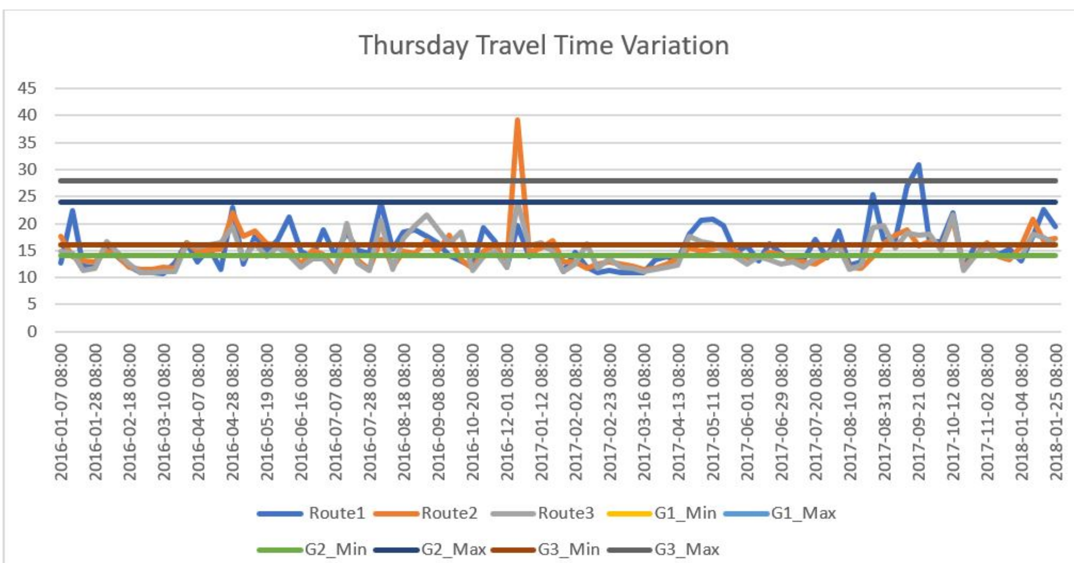

Figure 18: Thursday Travel Time Variation

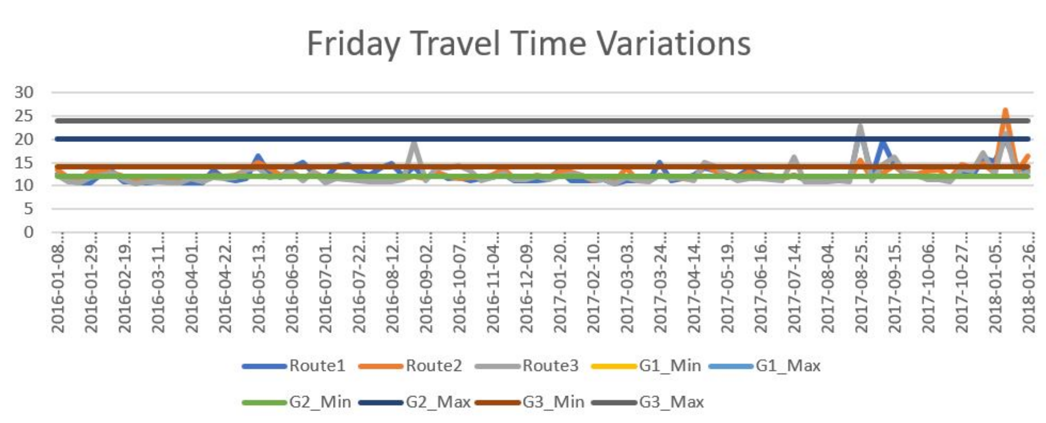

Figure 19: Friday Travel Time Variation

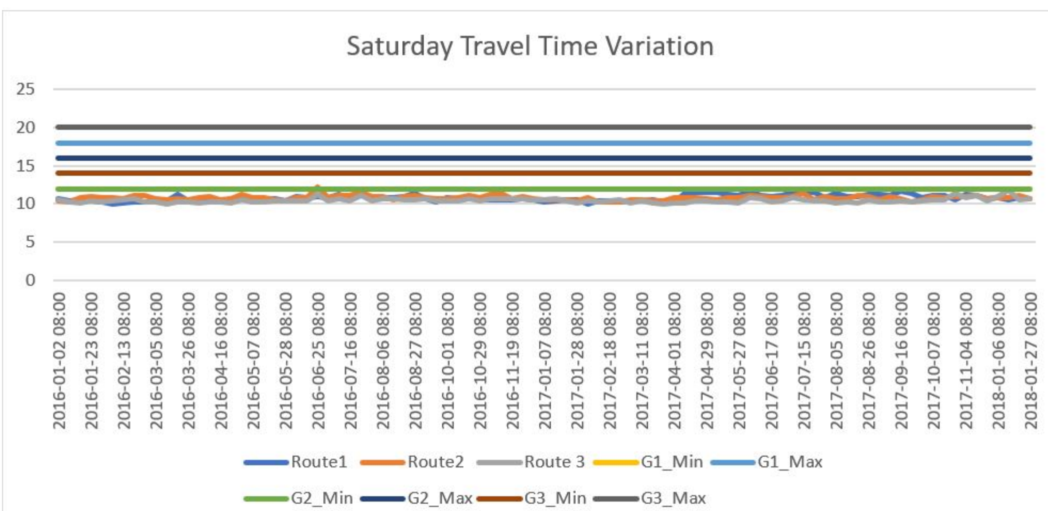

Figure 20: Saturday Travel Time Variation

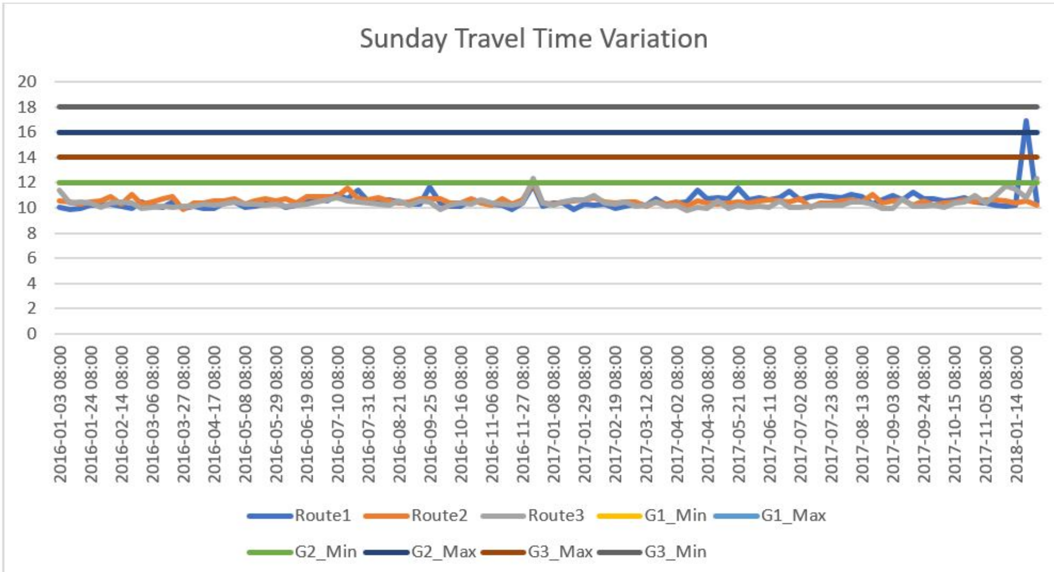

Figure 21: Sunday Travel Time Variation

4.4 Finding the Best routes by Reliability measures using Travel Time Reliability Estimation System

The routes that are available in the travel time reliability estimation system in them we are having doubt which route is reliable and best to travel. Our question is to find the best routes among the possible routes from source to destination when user or driver starts at a point. In order to find the reliability measure we have to consider the following reliability values like Average Travel Time and 95th percentile travel time. In order to find the best routes we can make some comparisons between the defined routes using the networks that we defined. So here we used to calculate the reliability values based on history data for all the weekdays from November 12 through 16.fig 22 shows the weather report for the same week. Based on the weather condition using TeTRES system, calculated the average travel time and 95th percentile travel time for all weekdays.From the results we can conclude that the values with lowest Average travel time and 95th percentile travel time is considered to be the most reliable routes and best to travel. The algorithm to find the best route is first will consider the 95th percentile travel time for all possible routes in them will select the least reliability value. If their is any tie between the routes in addition to this will go for considering the Average travel time for finding the best route.

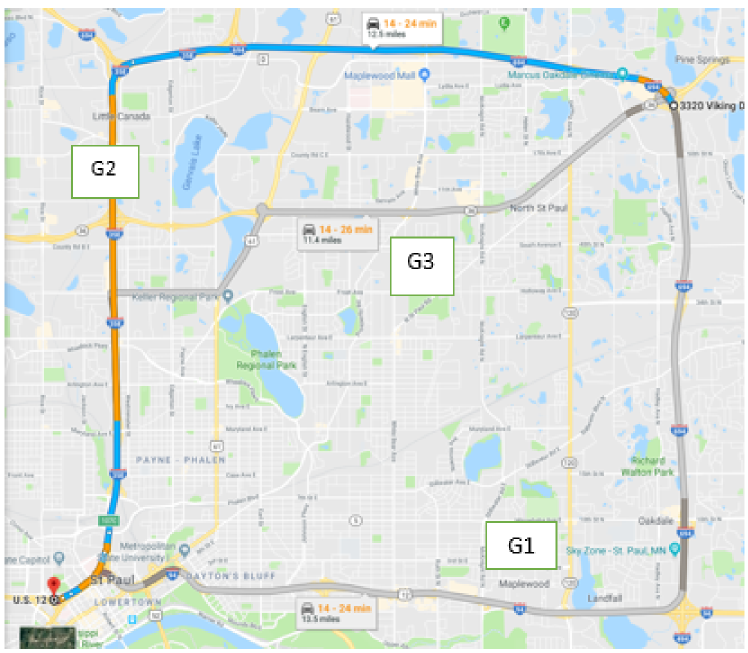

Figure 22: Google map possible Routes from start to end

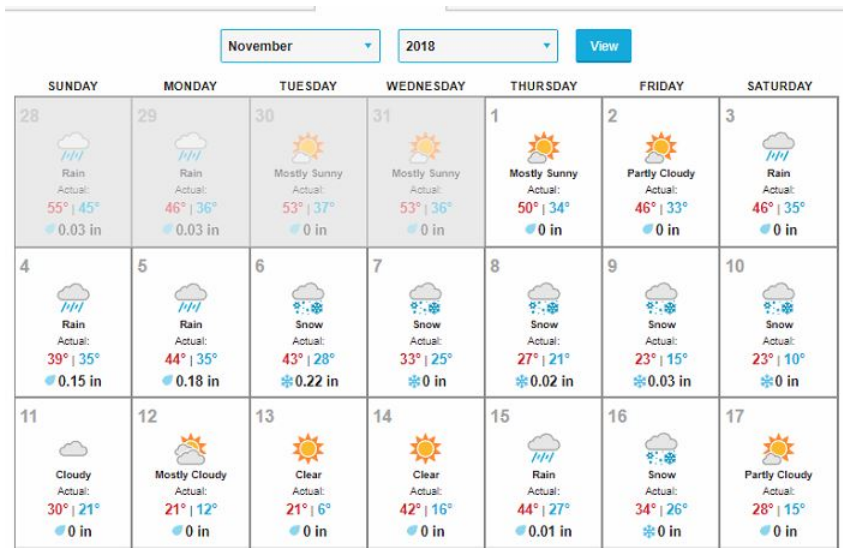

Figure 23: weather report for November 2018

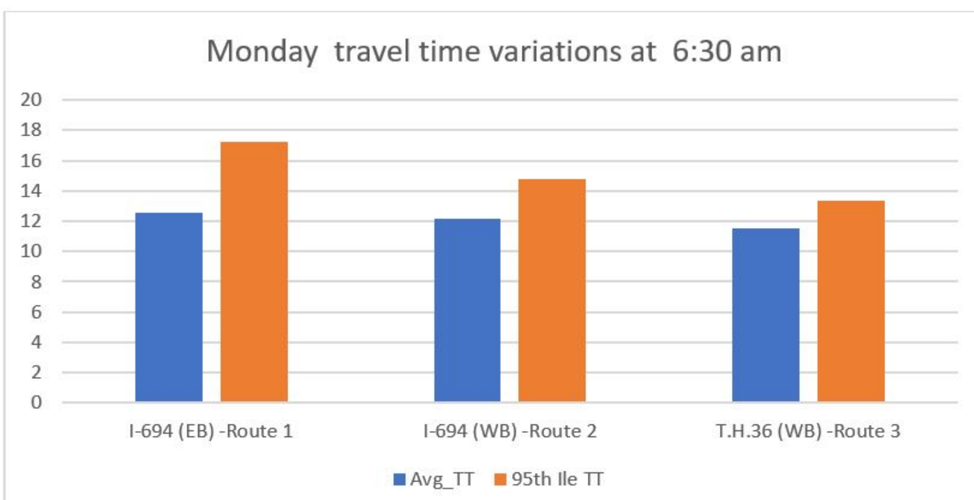

Figure 24: Monday Travel Time variation at 6:30 am

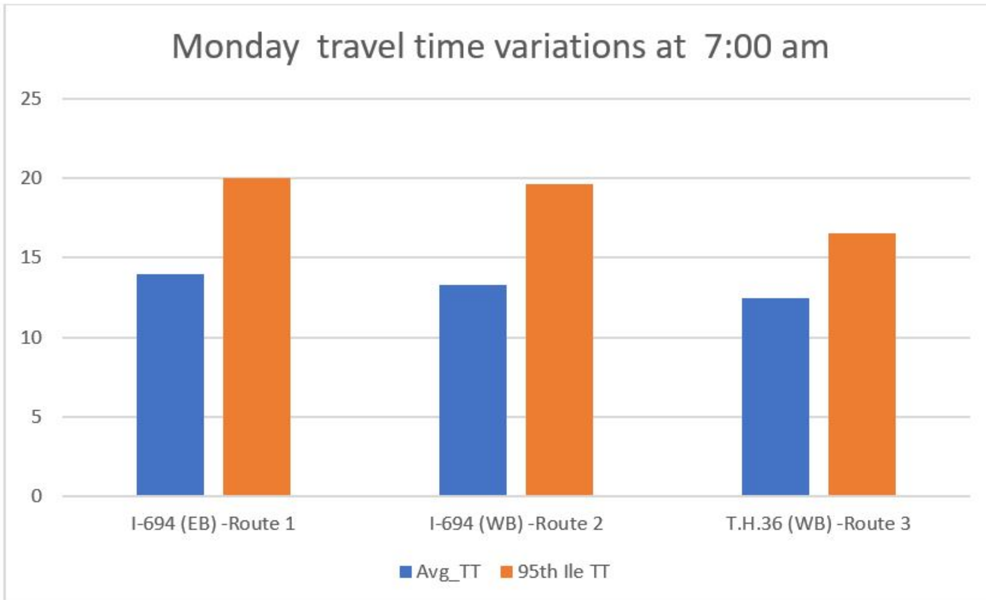

Figure 25: Monday Travel Time variation at 7:00 am

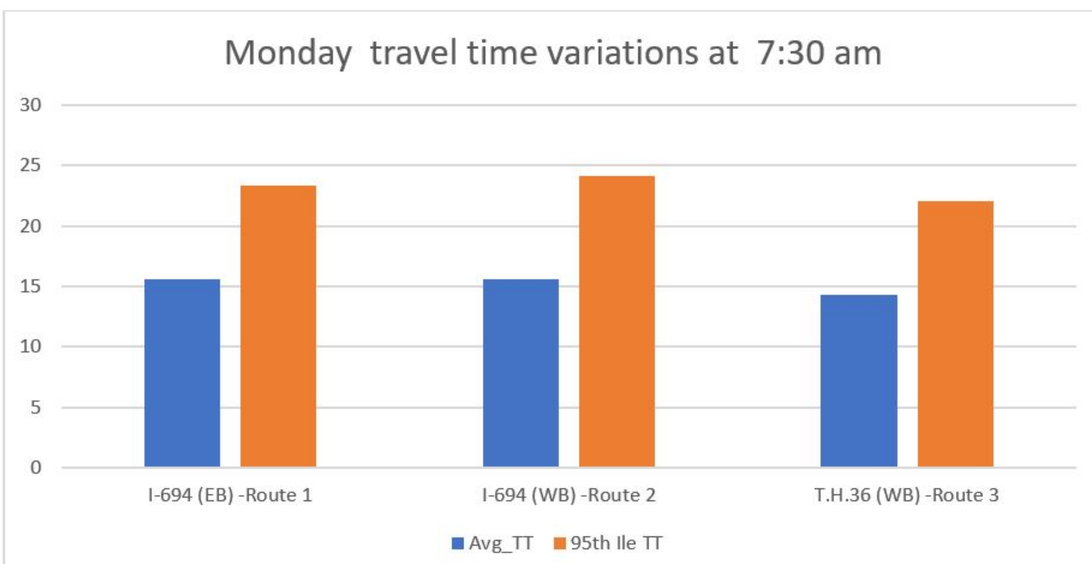

Figure 26: Monday Travel Time variation at 7:30 am

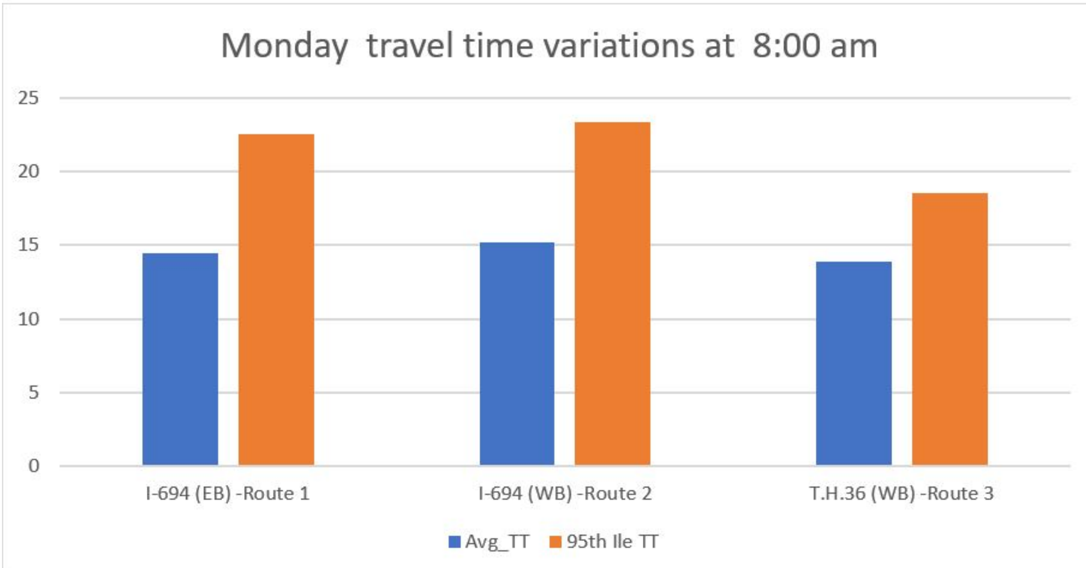

Figure 27: Monday Travel Time variation at 8:00 am

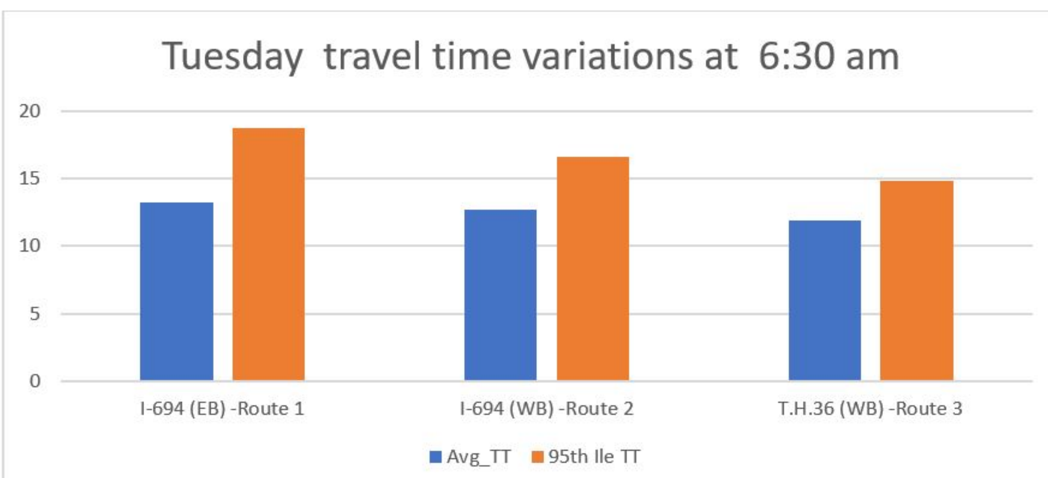

Figure 28: Tuesday Travel Time variation at 6:30 am

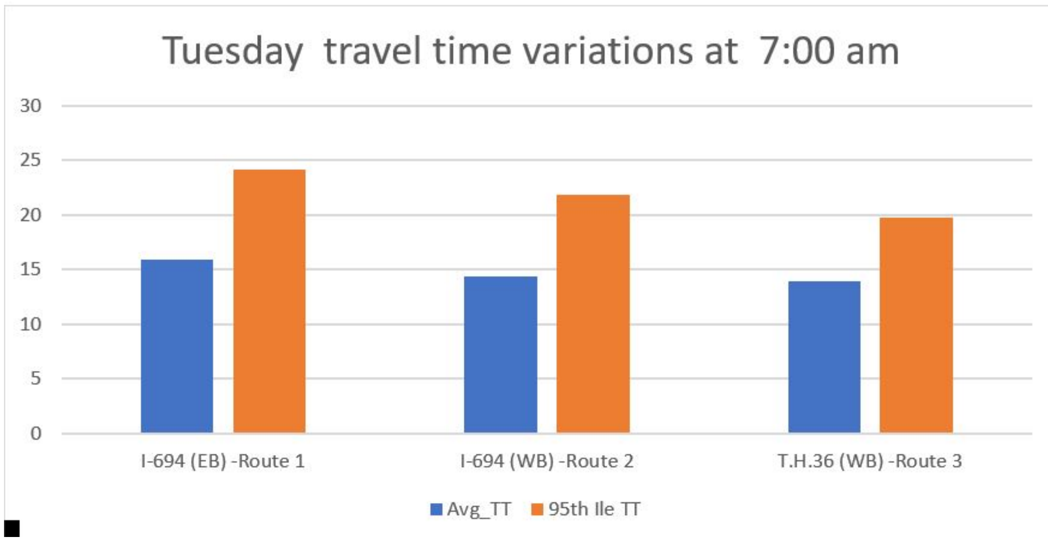

Figure 29: Tuesday Travel Time variation at 7:00 am

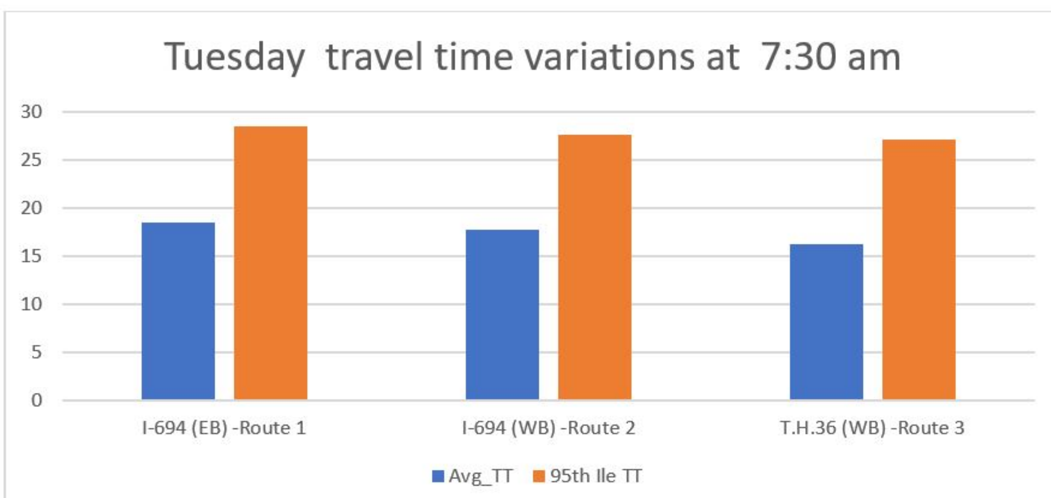

Figure 30: Tuesday Travel Time variation at 7:30 am

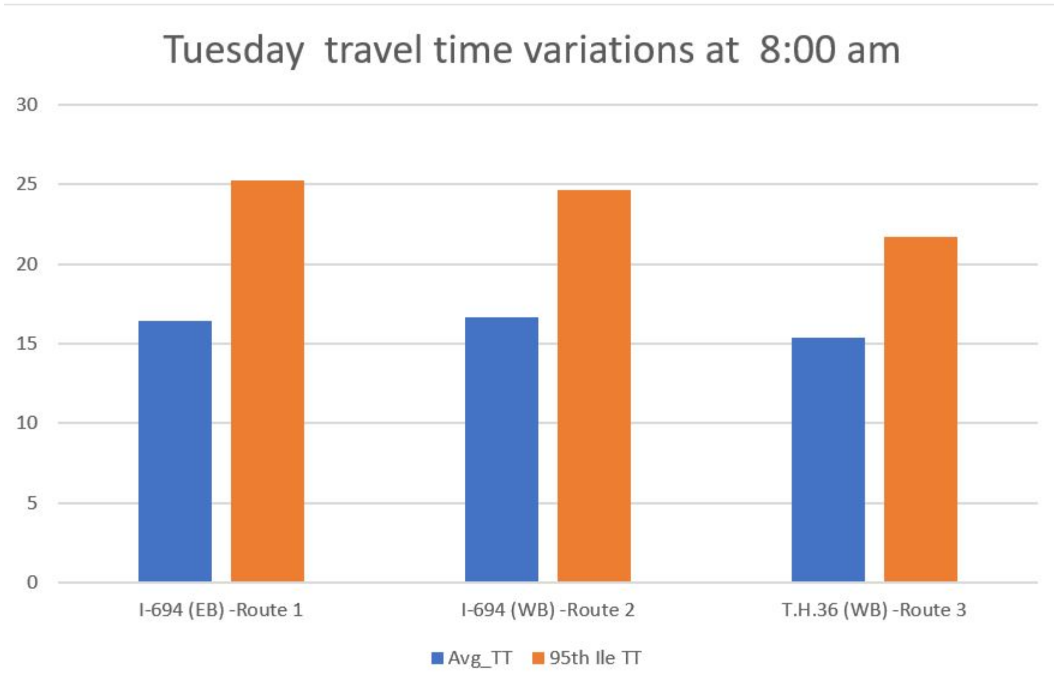

Figure 31: Tuesday Travel Time variation at 8:00 am

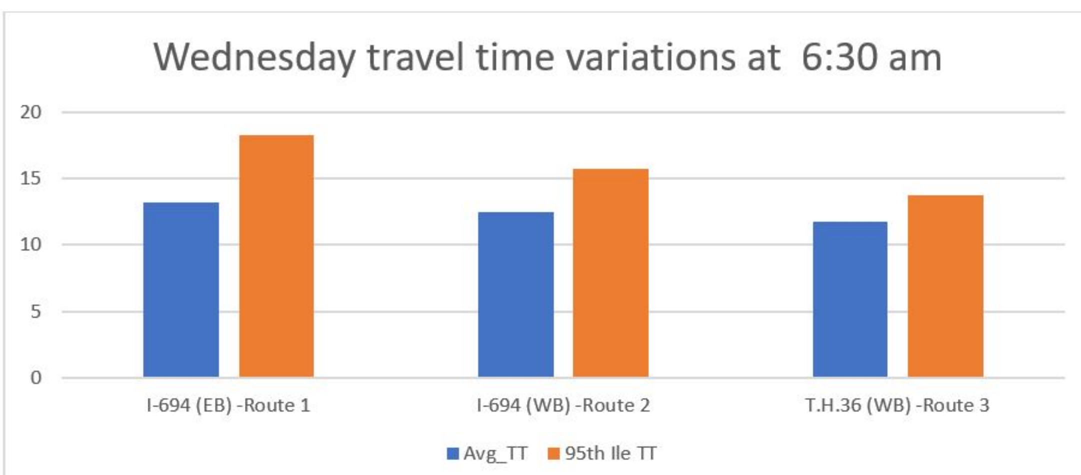

Figure 32: Wednesday Travel Time variation at 6:30 am

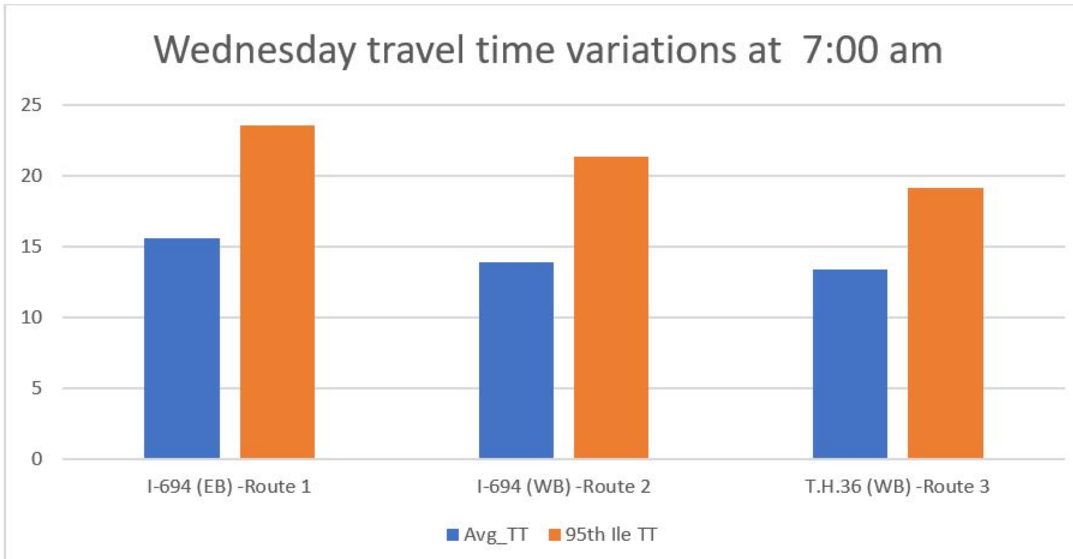

Figure 33: Wednesday Travel Time variation at 7:00 am

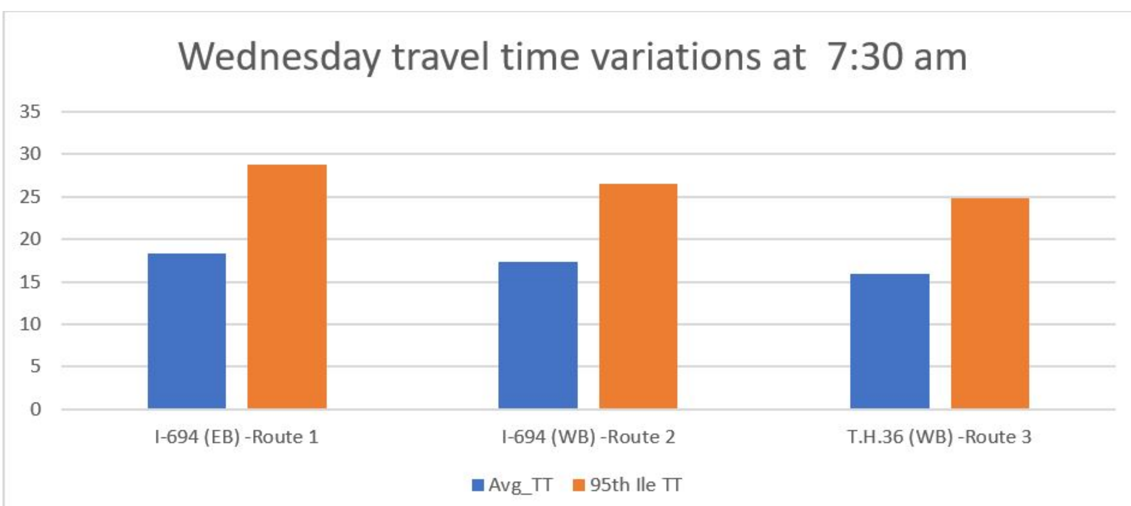

Figure 34: Wednesday Travel Time variation at 7:30 am

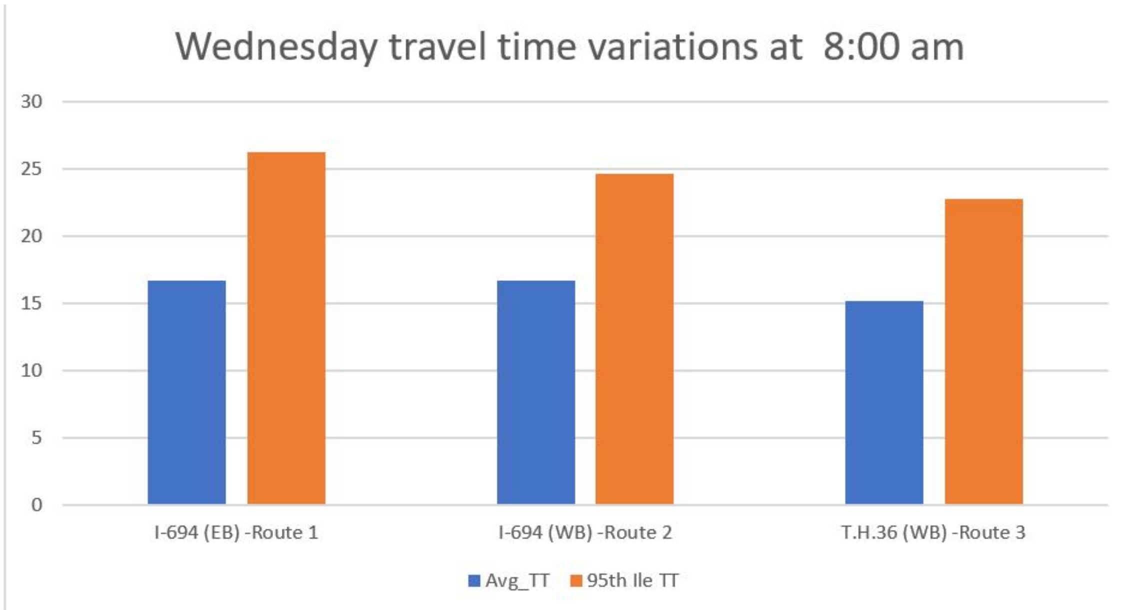

Figure 35: Wednesday Travel Time variation at 8:00 am

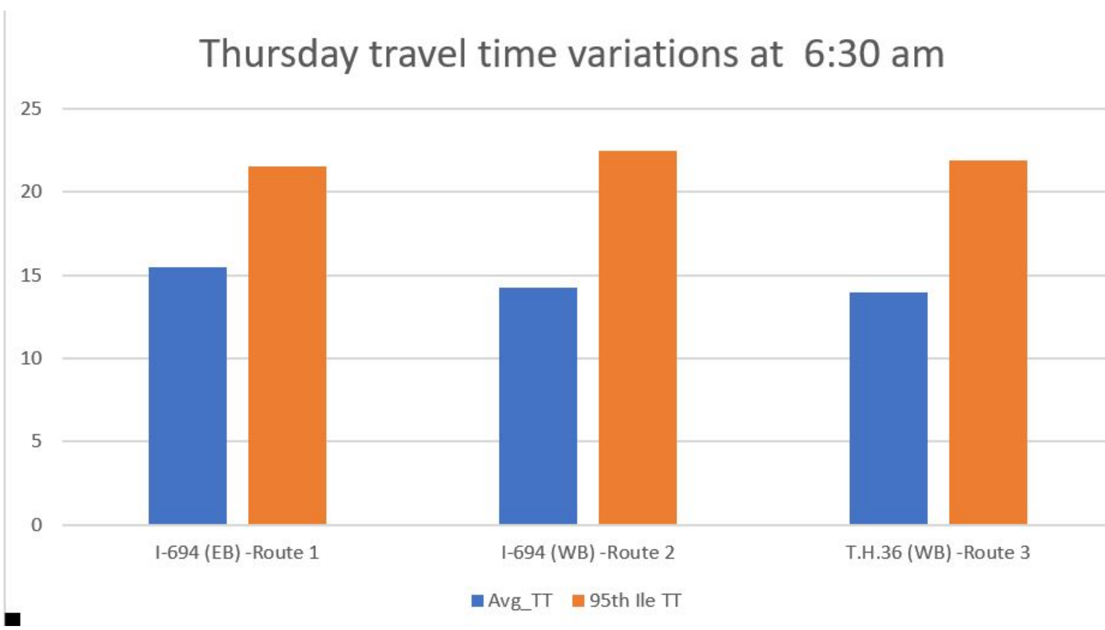

Figure 36: Thursday Travel Time variation at 6:30 am

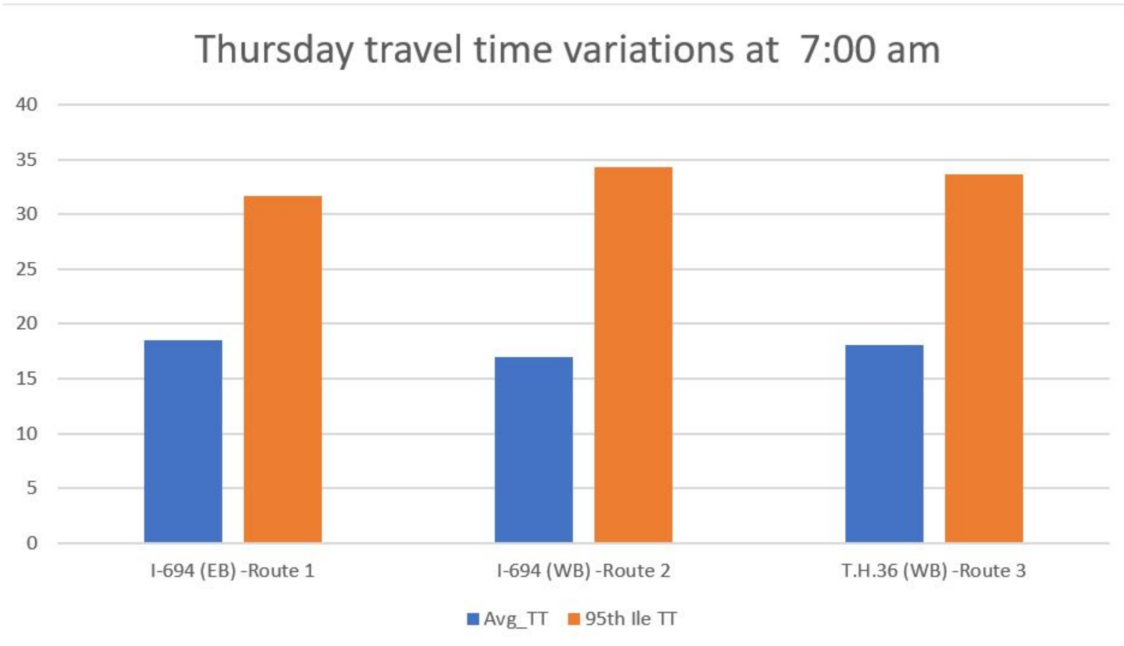

Figure 37: Thursday Travel Time variation at 7:00 am

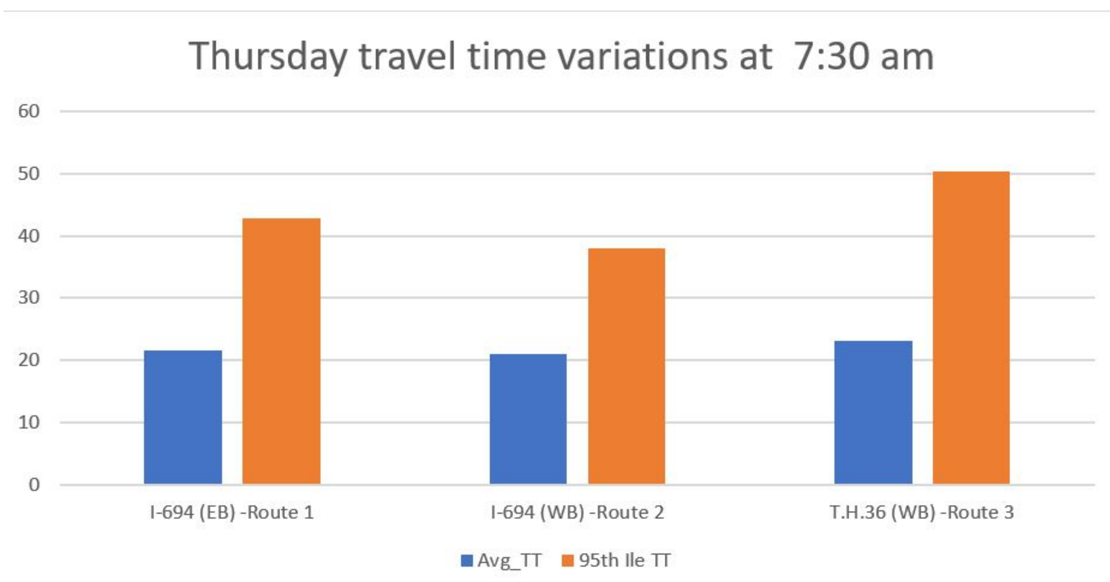

Figure 38: Thursday Travel Time variation at 7:30 am

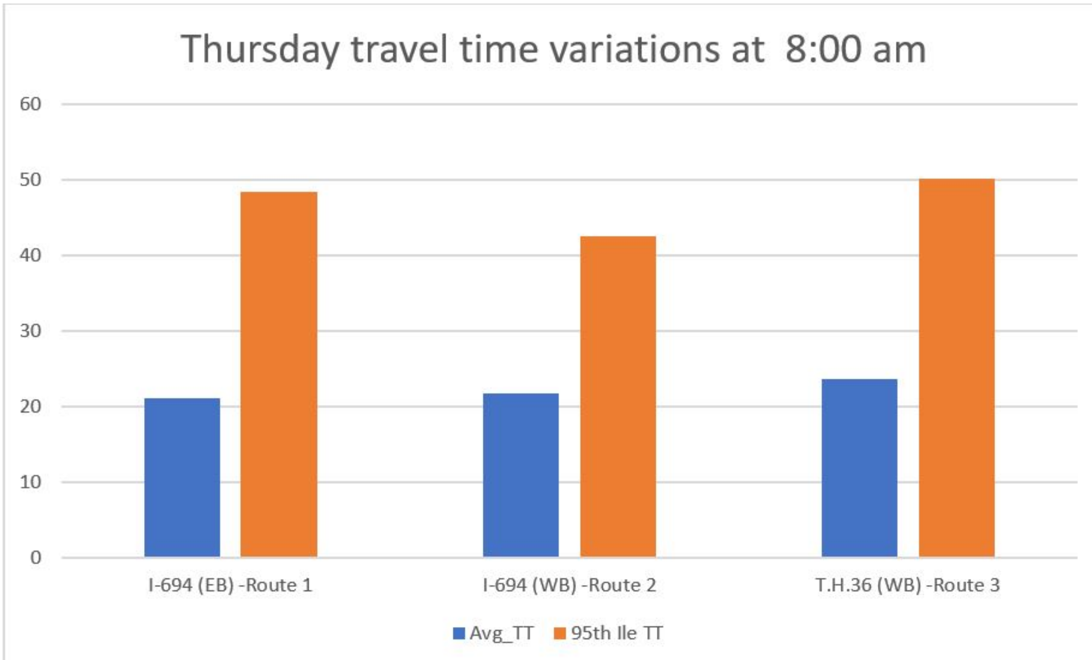

Figure 39: Thursday Travel Time variation at 8:00 am

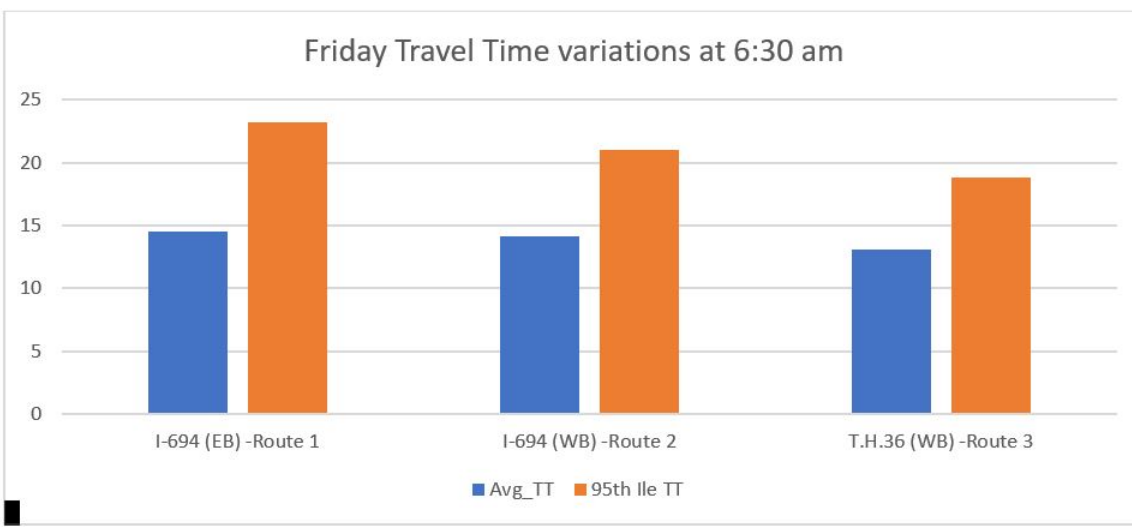

Figure 40: Friday Travel Time variation at 6:30 am

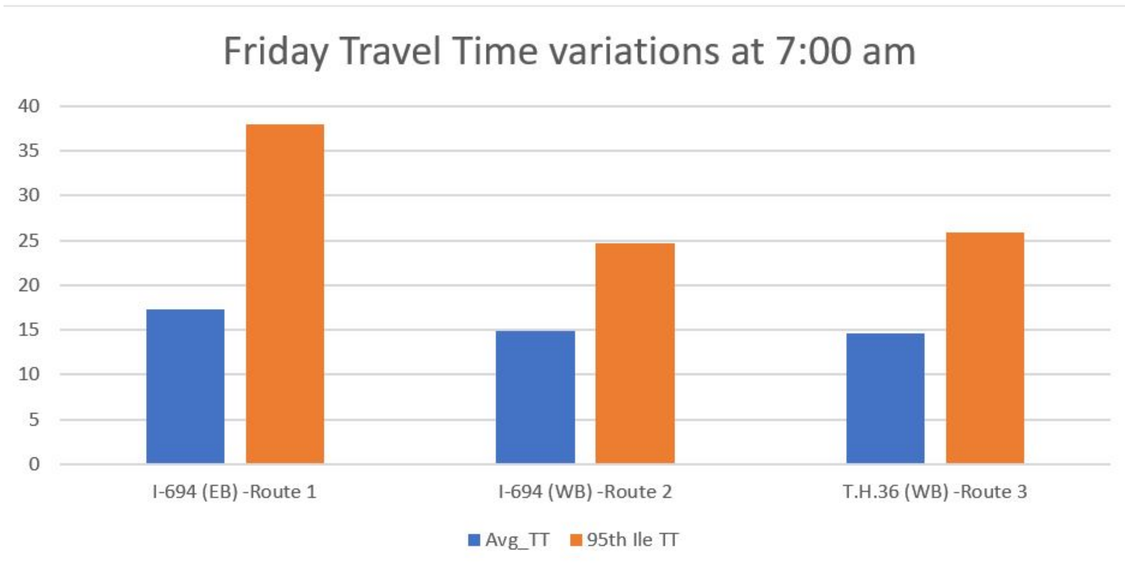

Figure 41: Friday Travel Time variation at 7:00 am

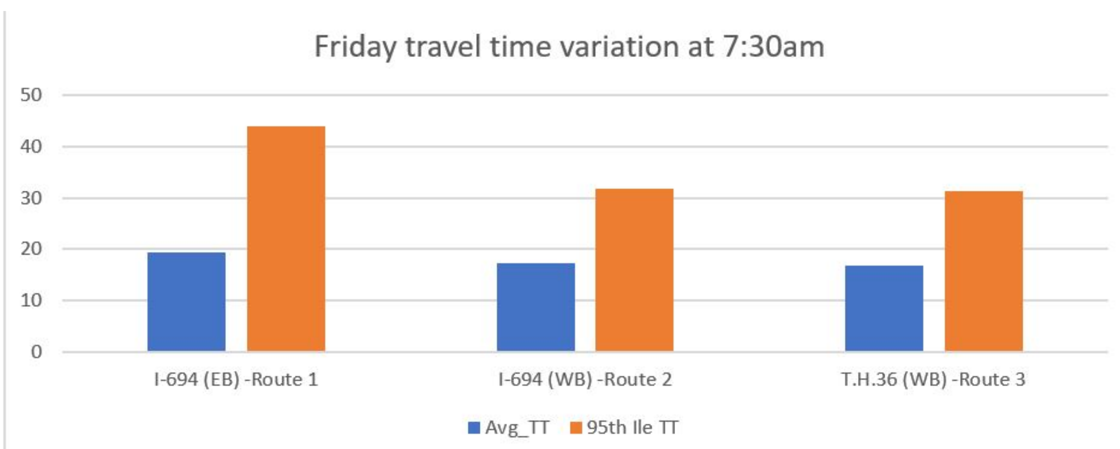

Figure 42: Friday Travel Time variation at 7:30 am

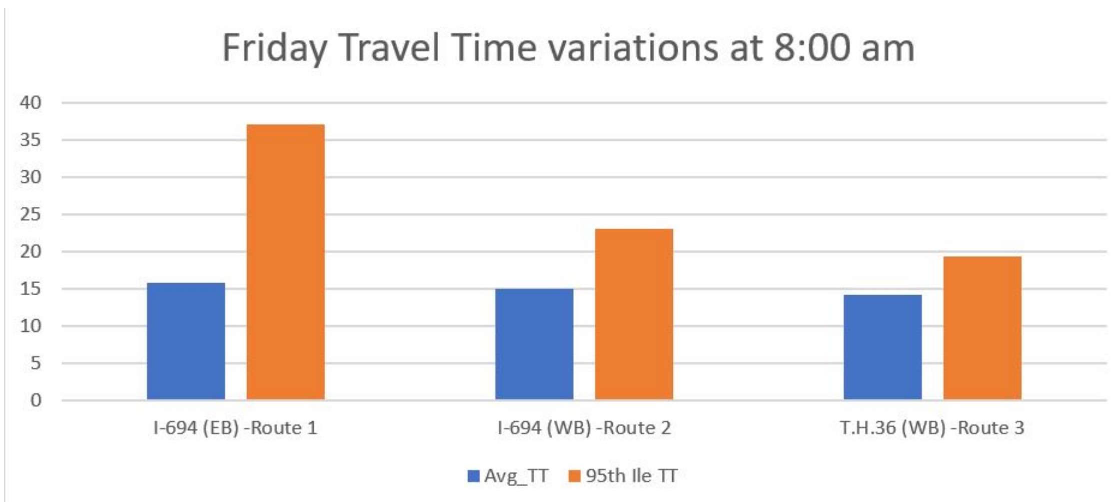

Figure 43: Friday Travel Time variation at 8:00 am

CHAPTER 5

CONCLUSION

A key element in building smart cities is a reliable traffic network, where efficient mobility services can be provided with consistent travel times in a time-variant environment. Developing such a network requires an efficient estimation of the travel-time reliability measures responding to various operating conditions and strategies, so that the causal relationship between the reliability measures and the operational strategies can be identified for a given network. This paper presented a travel-time reliability estimation system, which integrates multiple data sets and determines the various types of the travel-time reliability measures under different operating conditions for a given network. The system was applied to evaluate the effects of two operational changes in the metro freeway network in Minnesota on the travel-time reliability. The comparison of the reliability measures before and after each operational change clearly shows the substantial improvements in terms of the travel-time variability and the congestion severity in a given network. Future work includes the modeling the causal relationship between the travel-time reliability and specific operational strategies for a given traffic system.

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VITA

Avinash Sankarasetty completed his bachelors degree in Electrical and Electronics Engineering from Pace Institute of Technology and Sciences in ongole, affiliated to Jawaharlal Nehru Technological University in Kakinada, India. He started his masters in Computer Science at the University of Missouri-Kansas City (UMKC) in August 2016, with an emphasis on Data Sciences and graduates in December 2018. While he was studying at UMKC, he worked as a software developer Intern at University of Minnesota from May 2018 to August 2018. Upon completion of his requirements for the Masterâs Program, he will works as a Software Engineer at Cerner Corporation.