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USE OF MULTISENSOR DATA IN MODELING FREEWAY TRAVEL TIME RELIABILITY

Final Report

by

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EXECUTIVE SUMMARY

Travel time reliability (TTR) is an important measure which has been widely used to represent the traffic conditions on freeways. Accurately modeling travel time reliability is very important for both transportation agencies and roadway users. Nowadays anonymous vehicle probe data have been greatly improved in both data coverage and data fidelity, and thus have become a reliable source for freeway travel time reliability analysis. However, in most cases, TTR data are analyzed at the segment level in the short-term, which may not be able to account for the TTR variability characteristics for the whole section in the long-term. The goal of this project is to develop a systematic approach to analyzing TTR of roadway segments along a corridor in the long-term. Specific objectives are to: 1) Select the most appropriate TTR measure, 2) Select typical segments based on historical TTR ratings, and 3) Analyze the TTR of selected segments with the consideration of time of day, day of week, year and weather, and 4) Predict the TTR and compare it with the ground truth data.

To achieve the goal, a comprehensive review of the literature is conducted and previous experience in determining factors influencing TTR is carefully examined and synthesized. A list of candidate TTR measures are also identified, evaluated and compared. The most appropriate TTR measure is selected for use in the TTR analysis. A number of influential factors are considered when analyzing TTR, which include, but are not limited to, time of day, day of week, year, segment location and weather. Finally, a simple linear regression model and a time-series model are developed and used to predict the TTR on a freeway corridor. This report focuses on the long-term travel time reliability analysis and intends to present data analysis results to help transportation planners make informed decisions.

Chapter 1. Introduction

1.1 Problem Statement

Travel time reliability (TTR) is an important measure which has been widely used to represent the traffic conditions on freeways. Accurately modeling travel time reliability is very important for both transportation agencies and road users. Nowadays anonymous vehicle probe data have been greatly improved in both data coverage and data fidelity, and thus have become a reliable source for freeway travel time reliability analysis. However, in most cases, TTR data are analyzed at the segment level in the short-term, which may not be able to account for the TTR variability characteristics for the whole section in the long-term. The goal of this project is to develop a systematic approach to analyzing TTR of roadway segments along a corridor in the long-term. To do so, a number of influential factors will be considered when analyzing TTR in this project.

1.2 Motivation of Study

The purpose of this project is to develop a systematic approach to illustrating how TTR distributes and varies with respect to time of day, day of week, year, and weather. Case studies are conducted to present different TTR variability patterns under different conditions. The analysis of TTR and the prediction methodology can also greatly help the decision makers plan, design, operate, and manage a more efficient highway system.

1.3 Objectives of Study

Specific objectives are to: 1) Select the most appropriate TTR measure, 2) Select typical segments based on historical TTR ratings, and 3) Analyze the TTR of selected segments with the consideration of time of day, day of week, year and weather, and 4) Predict the TTR and compare it with the ground truth data. This report focuses on the long-term travel time reliability analysis step by step and to present data analysis results to help the transit planners make informed decisions.

1.4 Report Overview

The remainder of this report is organized as follows: Chapter 2 provides general information about TTR, including several definitions of TTR and a list of TTR measures. This chapter also reviews the previous research studies on TTR analysis, including those on the basis of travel time distribution, those at the network level, those with the consideration of incidents/weather and those with the consideration of multiple influencing factors. Chapter 3 presents data preparation and processing steps. It starts with a primary analysis of the probe vehicle data of the select Interstate-77 segments in Charlotte, NC. The weather data information and the process to combine these two datasets are also discussed. Chapter 4 presents the TTR variability pattern analysis. The selection of TTR measures is discussed first. This is followed by the study location identification. The analysis of long-term TTR variability pattern with the consideration of day of weak and weather is then discussed. Chapter 5 discusses the prediction of TTR. It starts with a brief introduction of the linear regression model and the time-series model used in this study. The prediction results on each select segment are then described. Chapter 6 concludes the report with a summary of the findings and some discussions about possible improvements to enhance current practices. Future research directions are also given.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides a comprehensive review of various aspects related to TTR studies, including TTR definitions, existing TTR measures, TTR modeling methodologies, etc. This should give a clear picture of existing concepts of TTR, the advantages and disadvantages of various TTR measures, and current efforts toward the modeling of TTR.

The following sections are organized as follows. Section 2.2 presents several definitions of TTR, followed by the presentation of a list of TTR measures in section 2.3. Section 2.4 gives a comprehensive review of existing methods of TTR analysis, which include travel time distribution-based studies, network level TTR studies, TTR analysis with the consideration of incidents/weather studies and TTR analysis with the consideration of multiple influencing factors. Finally, section 2.5 concludes this chapter with a summary.

2.2 Travel Time Reliability Definitions

Different definitions of travel time reliability have been developed in different studies. It will be helpful to review the existing definitions in different studies to clarify the concept of travel time reliability and its measurement. This section briefly reviews existing 'reliability' and 'travel time reliability' definitions. Table 2.1 provides a summary of existing travel time reliability definitions in chronological order.

Charles (1997) defined reliability as "*the probability that a component or system will perform a required function for a given period of time when used under stated operating conditions. It is the probability of a non-failure over time*." This definition is similar to the other definitions used in reliability engineering (Elefteriadou and Cui, 2007).

In the transportation area, there are several different definitions of reliability developed including system reliability, travel time reliability and network reliability. Turner et al. (1996) defined trip time reliability as the range of travel times experienced during a large number of daily trips. This definition considered the range of travel times. However, this study did not specify when 'failure' has occurred. In addition, it did not provide a good assessment of "*actual operating conditions, the presence and duration of congestion, or the percent of time the facility operates as expected*."

NCHRP report 398 (1997) defined travel time reliability as "*the impact of non-recurrent congestion on the transportation system*." In NCHRP report 399 (1998), travel time reliability was defined as "*a measure of the variability of travel time*". California Transportation Plan (1998) defined reliability as "*the level of variability between the expected travel time and the actual travel time experienced*." Florida DOT (2011) defined the reliability on a highway segment as "*the percent of travel that takes no longer than the expected travel time plus a certain acceptable additional time*." They also defined three major components of reliability: *travel time, expected travel time, and acceptable additional time*. AASHTO's freight report (2002) defined reliability as *"the percent of on-time performance for a given time schedule"*, and this definition was provided for freight transportation. Recker et al. (2004) defined both path and Origin-Destination (OD) travel time reliability. Specifically, the path travel time reliability was defined as *"the probability that the travel time of a given path is within an acceptable threshold"* and the OD travel time reliability was defined as "*the probability that the weighted average travel time of a given OD pair is within an acceptable threshold*."

The Federal Highway Administration (FHWA) (2012) gave a formal definition of travel time reliability, which is: "*the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day*." SHRP 2 Project (2014) defined travel time reliability as "*the variability in travel times that occur on a facility or for a trip over the course of time;* and *the number of times (trips) that either "fail" or "succeed" in accordance with a predetermined performance standard or schedule*."

Table 2.1: Summary of Existing Travel Time Reliability Definitions

Author/Agency	Year	Reliability/Travel Time Reliability Definition
Turner et al.	1996	The range of travel times experienced during a large number of daily trips.
Charles	1997	The probability that a component or system will perform a required function for a given period of time when used under stated operating conditions. It is the probability of a non-failure over time.
NCHRP Report 398	1997	The impact of non-recurrent congestion on the transportation system.
NCHRP Report 399	1998	A measure of the variability of travel time.
California Transportation Plan	1998	The level of variability between the expected travel time and the actual travel time experienced.
AASHTO's Freight Report	2002	The percent of on-time performance for a given time schedule.
Elefteriadou and Cui	2007	The probability of a device performing its purpose adequately for the period of time intended under the stated operating conditions.
Florida DOT	2011	The percent of travel that takes no longer than the expected travel time plus a certain acceptable additional time.
FHWA	2012	The consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day
Vandervalk et al. (SHRP 2 project)	2014	The variability in travel times that occur on a facility or for a trip over the course of time; and the number of times (trips) that either "fail" or "succeed" in accordance with a predetermined performance standard or schedule

2.3 Travel Time Reliability Measures

This section introduces the characteristics of different travel time reliability measures. Table 2.2 provides a summary of the TTR measures discussed in this section in chronological order.

2.3.1 Basic Statistics Measures

(1) Standard Deviation

Standard deviation is a well-defined classical statistical measure and usually used as a proxy for other reliability measures (Charles, 1997). However, the use of standard deviation as a reliability performance measure was discouraged by some studies (U.S. DOT guide, 1996 and NCHRP Report 618, 2008) because "*it is not easily understood by nontechnical audiences nor easily related to everyday commuting experiences, and it treats early and late arrivals with equal weight, whereas the public cares much more about late arrival.*"

(2) Coefficient of Variation (CV)

The average travel time and standard deviation values can be combined and used to generate a value which is called coefficient of variation (CV). The CV is calculated as the ratio of the standard deviation to the mean. The use of CV is also discouraged by some studies with the same concern as about the usage of standard deviation. However, it still being utilized by some researchers.

$$\mathrm{CV} = \frac{\text{Standard deviation}}{\text{Average travel time}}$$

(3) Percent Variation

The average travel time and standard deviation values can also be combined in a ratio to produce a value that was recommended by the 1998 California Transportation Plan.

$$\text{Percent variation} = \frac{\text{Standard deviation}}{\text{Average travel time}} \times 100\% = \mathrm{CV} \times 100\%$$

This measure has the same mathematical characteristics as the CV. However, it is easier for the public to understand percent variation as it is expressed as a percentage of average travel time. This measure was adopted by the 1998 California Transportation Plan (1998) and recommended by Lomax et al. (1997) and NCHRP Report 618 (2008).

(4) Variability Index

The variability index is a ratio of *peak to off-peak variation in travel conditions*. The index is calculated as *"a ratio of the difference in the upper and lower 95% confidence intervals between the peak period and the off-peak period"* (Lomax et al., 1997 and Florida DOT, 2011).

$$\text{Variability Index} = \frac{\text{Difference in peak period confidence intervals}}{\text{Difference in off peak period confidence intervals}}$$

Because the interval differences in the off-peak periods are usually lower than the differences in the peak period, the value of variability index is usually greater than 1.

2.3.2 FHWA TTR Measures

There are four TTR measures introduced and recommended by FHWA.

(5) 90th/95th Percentile Travel Times

90th/95th percentile travel times are both basic TTR measures which have been widely used in the world. These indexes indicate how much delay will be on the heaviest travel days and were introduced as one of the four recommended travel time reliability measures by FHWA. The 90th or 95th percentile travel times are usually reported in minutes and seconds. They could be easily understood by roadway users who are familiar with their trips.

However, the disadvantage of this measure is "*not being easily compared across trips with the consideration of different trip lengths*." It is also difficult to combine route travel times into a citywide average.

(6) Buffer Index (BI)

Buffer index (BI) represents the extra time required by the travelers to arrive on time in addition to the travel time under average conditions and was introduced as one of the four recommended measures by FHWA. This extra time is added to account for any unexpected delay. The BI is expressed as a percentage, and its value increases as reliability gets worse. Traditionally, arithmetic average travel time is used to represent the travel time under average conditions, and the BI is defined by the difference between the 95th percentile travel time and the average travel time. For example, to ensure on-time arrival, a BI of 50 percent means that, for a 30-minute average travel time, a traveler should budget an additional 15 minutes (30 minutes × 50% = 15 minutes). 15 minutes here is called the buffer time. The BI is computed as the difference between the 95th percentile travel time and average travel time, divided by the average travel time. The equation is shown below:

$$\text{BI} = \frac{\text{95th percentile time} - \text{average travel time}}{\text{average travel time}} \times 100\%$$

A recent SHRP 2 report suggested that the median travel time can also be used to define the BI (Vandervalk et al., 2014).

(7) Planning Time Index (PTI)

Planning time index (PTI) was also introduced as one of the four recommended measures by FHWA. It represents *the total time needed to plan for an on-time arrival 95% of the time (total travel time that should be planned when an adequate buffer time is included),* *computed as 95th percentile travel time divided by free-flow travel time.* The equation is presented below:

$$\text{PTI} = \frac{\text{95th percentile travel time}}{\text{free flow travel time}}$$

The PTI differs from the BI and it compares near-worst case travel time with that under free-flow traffic condition. For example, a PTI of 1.50 means that, for a 20-minute trip under light traffic condition, the total time that should be planned for the trip is 30 minutes (20 minutes × 1.50 = 30 minutes). PTI is a useful measure as it can be directly combined and used with the travel time index.

(8) Frequency of Congestion (FOC)

Frequency of congestion (FOC) is a measure introduced as one of the four recommended travel time reliability measures by FHWA, which represents the frequency of congestion exceeding some expected threshold. It can be typically expressed as the percent of days/time that travel times exceed a time threshold x or travel speeds fall below a speed threshold y. The FOC is relatively easy to compute if continuous traffic data are available, and it is typically reported on weekdays during peak traffic periods.

2.3.3 Other Measures

(9) Skew of travel time distribution

The skew statistics is a robust measure introduced by Van Lint and Van Zuylen (2005). It is defined as the ratio of the difference between the 90th percentile travel time and the median and the difference between the median and the 10th percentile travel time. The equation is given below:

$$\lambda^{skew} = \frac{\text{T90} - \text{T50}}{\text{T50} - \text{T10}}$$

(10) Width of travel time distribution

The width statistics is a robust measure introduced by Van Lint and Van Zuylen (2005). It is defined as the ratio of the difference between the 90th percentile travel time and the 10th percentile travel time and median travel time. The equation is shown below:

$$\lambda^{width} = \frac{\text{T90} - \text{T10}}{\text{T50}}$$

(11) Misery index

Misery Index is a measure that can indicate the length of delay of only the worst trips. It is usually computed by subtracting the average travel rate from the upper 20 percent of travel rates. This yields the time difference between the average trip and the slowest 20 percent of trips. The equation is below:

$$\text{Misery index} = \frac{\text{Average travel rate (Top 20\% trips)}}{\text{Average travel rate}} - 1$$

Table 2.2: Summary of Travel Time Reliability Measures

Measure	Author/Agency	Equation
Standard deviation	Dowling et al. (2009); Pu (2011)	Standard deviation
Coefficient of variation	Pu (2011)	$\text{Coefficient variation} = \frac{\text{Standard deviation}}{\text{Average travel time}}$
Present variation	1998 California Transportation Plan; Lomax et al. (1997); NCHRP Report 618 (2008)	$\text{Percent variation} = \frac{\text{Standard deviation}}{\text{Average travel time}} \times 100\%$
Variability Index	Lomax et al. (1997); Albert (2000)	$\frac{\text{Difference in peak period confidence intervals}}{\text{Difference in off peak period confidence intervals}}$
90th/95th Percentile Travel Times:	FHWA	90th/95th Percentile Travel Times
Buffer Index	FHWA	$\frac{\text{95th precentile time} - \text{average travel time}}{\text{average travel time}} \times 100\%$
Planning Time Index	FHWA	$\frac{\text{95th percentile travel time}}{\text{free flow travel time}}$
Frequency of Congestion	FHWA	Frequency of trips exceeding a threshold value
Skew of travel time distribution	Van Lint and Van Zuylen (2005)	$\lambda^{skew} = \frac{\text{T90} - \text{T50}}{\text{T50} - \text{T10}}$
Width of travel time distribution	Van Lint and Van Zuylen (2005)	$\lambda^{width} = \frac{\text{T90} - \text{T10}}{\text{T50}}$
Misery Index	Lomax et al. (1997)	$\text{Misery index} = \frac{\text{Average travel rate (Top 20\% trips)}}{\text{Average travel rate}} - 1$

2.4 TTR Analysis Methods

Basically, TTR can be analyzed based on travel time distribution data only. However, to investigate the impacts of nonrecurring congestion on TTR, different sources of travel time variability including traffic incidents, inclement weather, and work zones were also studied by different researchers around the world. This section reviews these studies by classifying them into 5 categories including TTR studies based on travel time distribution only; Network level TTR studies; TTR studies with the consideration of weather impact; TTR studies with the consideration of incident impact and TTR studies with the consideration of multiple influencing factors.

2.4.1 TTR Studies Based on Travel Time Distribution

Research studies that used basic travel time distribution data to model TTR are reviewed in this section. **Error! Reference source not found.** provides a summary of the studies reviewed in this section in chronological order.

2.4.1.1 Van Lint and Van Zuylen's research work

Van Lint and Van Zuylen (2005) derived two time-reliability-metrics (skew and width) based on the 90th, 50th and 10th percentile of the day-to-day travel time data. Both metrics can make a clear distinction between different traffic flow conditions (congestion, free or transient). They could also identify the travel time reliability and congestion during a given time of day (TOD) and day of week (DOW) time period. The results could be used in discrete choice models and for travel time unreliability visualization on the map.

2.4.1.2 Saberi and Bertini's research work

Saberi and Bertini (2010) prioritized freeway segments with the help of TTR measures based on the archived loop detector data from the Interstate-5 freeway (24 miles long) in Portland, Oregon in the U.S. Several reliability measures were selected and examined using differential reliability maps and compared with travel-time-based measures. The authors found that the buffer time index and the coefficient of variance were the most consistent among the measures of reliability. Their research also showed that freeway segment correlations have high impacts on the variability of corridor travel time and should not be ignored. It was also found that different reliability measures presented different portraits of the reliability aspects on a freeway corridor. However, other factors contributing to the unreliability of travel times were not identified in this research study.

2.4.1.3 Yazici et al.'s research work

Yazici et al. (2012) developed a method to analyze TTR based on DOW and TOD patterns by utilizing GPS data collected from taxis in the New York City. The authors selected coefficient of variation (CV), skewness (λ_{skew}), and width of the distribution (λ_{var}) as the TTR measures and used the Classification and Regression Tee (C&RT) model for the determination of DOW-TOD periods for each selected TTR measure.

The results of the study showed that TTR exhibited time-varying patterns which could be identified during different DOW-TOD periods. Based on the analysis results, the authors found that the *"levels of reliability at the calculated periods generally did not agree well"*, which means that a reliable period identified based on one measure could be found to be an unreliable period using a different measure.

2.4.1.4 Eliasson's research work

Eliasson (2007) used data from the Stockholm's automatic camera system and developed a model for estimating travel time variability in terms of the mean travel time, length of link, and free flow travel time.

The author identified a stable relationship between the relative standard deviation of travel time (standard deviation divided by travel time) and the relative increase in travel time (travel time divided by free-flow travel time) and then estimated a function to predict how changes in congestion impact the TTR.

The author also investigated the relationship between travel time distribution and different TOD periods. The result showed that *"travel times are approximately normally distributed"* under severe congestion condition. However, the travel time distribution was skewed under low levels of congestion condition.

2.4.1.5 Emam and Ai-Deek's research work

Emam and Ai-Deek (2006) defined reliability as "*the probability that an entity will perform its intended function(s) satisfactorily or without failure for a specified length of time under the stated operating conditions at a given level of confidence*". Based on such definition, the TTR was expressed mathematically using the failure rate (hazard) function. Four different travel time distributions were tested in this study including Weibull, exponential, log-normal, and normal distribution. The Anderson-Darling (AD) goodness-of-fit statistics and error percentages were employed to evaluate model performances. As a result, the log-normal distribution provided the best model fit and was then used to predict TTR of freeway corridors. The proposed methodology was applied to estimate travel time reliability on the I-4 corridor in Orlando, Florida using real-world transportation data collected by dual-loop detectors.

The results indicated that it was more efficient to use the same day of the week (e.g., Mondays) in the estimation of TTR for a roadway segment than to use mixed data (i.e., data collected across multiple weekdays), because of the significant differences between traffic patterns across multiple weekdays. In addition, the researchers also noticed that the new reliability estimation method showed higher sensitivity to geographical locations, which reflects the congestion level and bottlenecks.

2.4.1.6 Sohn and Kim's research work

Sohn and Kim (2009) presented a method for predicting the dynamic variance in estimating link travel times. The authors adopted the autoregressive moving average-generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model and employed the generalized Pareto distribution (GPD) in the computation to overcome the *asymmetry in travel time distribution*.

The authors also used the travel time data which were obtained from the beacon-based probing system in Seoul and performed single and multiperiod predictions. The 90th, 95th, and 99th percentiles of travel times were selected as the TTR measures.

The analysis results showed that the ARMA-GARCH-GPD model was the most promising model for the first four sites. For the other sites without GPD, the ARMA-GARCH was good enough to obtain promising results.

2.4.1.7 Hainen et al.'s research work

Hainen et al. (2011) conducted a study to compute travel time based on the data collected from Bluetooth devices. To examine the impact of bridge closure in Indiana, US, the authors used data from media access control (MAC) addresses from Bluetooth-enabled devices to conduct travel time plots and identify congestion choke points. The authors also estimated the distribution of travel times on four alternate routes. The 25th and the 75th percentile travel times were used as the TTR measures to evaluate the effects of each choice.

This study indicated how to evaluate different route choice based on data collected from Bluetooth devices, sampling methodology and travel time reliability data.

2.4.1.8 Lei et al.'s research work

Lei et al. (2014) developed a path TTR estimation model considering the dynamic of shock waves using the probability-based method. The authors estimated two model parameters: distribution of travel time per unit distance and travel distances on different level of service (LOS) segments by using historical floating car data on Beijing's Third Ring Expressway.

Four LOS segments were taken as examples to explain the developed model. Finally, a comparison was made among the developed model, the generalized Pareto contrast model, and normal contrast model. The proposed model achieved higher prediction accuracy and significantly reduced the prediction range of travel time.

2.4.1.9 Zheng et al.'s research work

Zheng et al. (2016) utilized the data from Automated Number Plate Recognition (ANPR) cameras to study TTR on a corridor in Changsha, China. Two reliability measures (standard deviation and the skewness of travel time) were derived from the travel time distribution model. The authors also investigated the relationship between these two measures and the expected travel time to show the effects of changing travel states. The results showed that the linear relationship could be developed between Travel Time Standard Deviation (TTSD) and mean travel time and skewness.

However, the linear relationships between TTSD and the mean travel time and skewness were not same under different links/days. The regression parameters for a link also linearly depend on the link length.

2.4.1.10 Yang's research work

Yang (2016) developed an innovative freeway travel time estimation model based on the General Motors (GM) car-following model and verified the model with the travel time data in St. Louis, Missouri. As with travel time collection, the accuracy of the observed travel time and the optimal travel time data quantity should be determined before using the TTR data. Hasofer Lind - Rackwitz Fiessler (HL-RF) algorithm was used to calculate the reliability index. The corridor and network level TTRs were estimated during a specific TOD-DOW time period. The results of the developed model were compared with the results of Florida TTR method. As the anticipated travel time increases, the TTRs of both methods also increase. During peak hours, TTR generated from the proposed method is found to be lower than that generated from the Florida reliability method.

2.4.1.11 Wang et al.'s research work

Wang et al. (2017) utilized the GPS probe data to forecast freeway TTR. The authors investigated the relationships between TTR and roadway traffic density to forecast reliability under future traffic conditions. The modeling results indicated that vehicle speed distributions and TTR which was quantified by speed distribution CV via GPS data were affected by different traffic conditions. The larger roadway density resulted in lower travel speed and lower reliability. This result also revealed that the distribution of CV is strongly associated with segment density. The authors pointed that "*travel time reliability can be forecasted based on the relationship between CV and density when future roadway density is available or predictable*."

2.4.1.12 Chen et al.'s research work

Chen et al. (2017) proposed a copula-based approach, which incorporated the stochastic characteristics of segments travel time to model arterial travel time distribution. The authors examined different types of copula models and empirically analyzed segments correlation. Based on the estimated parameters of the models, the best copula model was selected and was also examined at two study sites at last. Skewness and width were selected as the path TTR measures. The result was compared with the convolution model without capturing segments correlation. The developed model demonstrated its advantage on travel time distribution estimation. Thus, the estimated path TTR was also more accurate.

2.4.1.13 Guo et al.'s research work

Guo et al. (2010) proposed a multistate TTR modeling framework for travel time modeling and reporting. This model was based on the premise that "*travel time is dominated by the underlying traffic conditions*", which was a complex stochastic process and may contain multiple travel time states. Two levels of uncertainty were quantitatively assessed in the proposed model. The first level of uncertainty was the probability under a given traffic condition and the second level of uncertainty was the variation of travel time under each traffic condition. The proposed model provided an opportunity for a novel, easy-to-understand TTR reporting mechanism built upon existing reliability measures.

Table 2.3: Summary of TTR Studies Based on Travel Time Distribution

Year	Author	Location	Data Aggregation	Data Source	Study Periods	TTR Measure(s)	Modeling Algorithm
2005	Van Lint and Van Zuylen	Rotterdam, Netherlands	15-min	N/A	6 a.m.- 8 p.m.	λ^{skew}, λ^{width}	Piecewise linear speed–based (PLSB) trajectory algorithm
2007	Eliasson	Stockholm	15-min	Camera detectors	6:30 a.m.- 8:30 p.m.	Standard deviation	N/A
2006	Emam and Ai-Deek	Orlando, FL, US	5-min	RTMC	3:30 – 6:30 p.m.	Buffer index, Coefficient of variation	Weibull, exponential, lognormal, and normal distribution testing
2008	Sohn and Kim	Seoul, Korea	N/A	Beacon-based probing system	N/A	Travel time index Buffer index	Autoregressive moving average-generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model
2010	Guo et al.	San Antonio, TX, US	N/A	Automatic vehicle identification (AVI) stations	6:00 - 10:00 a.m. 3:00 - 7:00 p.m.	Standard deviation, 90th percentile travel time	Maximum likelihood function; Mixture normal model
2010	Saberi and Bertini	Portland, Oregon, US	5-min	Inductive loop detectors	3 p.m. – 6 p.m.	Buffer index, Coefficient of variation	Standard midpoint algorithm
2011	Hainen et al.	Indiana, US	N/A	Bluetooth-enabled devices	N/A	25th, 50th, and 75th percentile travel time	N/A
2012	Yazici et al.	New York City, US	N/A	NYC Taxis GPS data	N/A	Coefficient of variation, λ^{skew}, λ^{width}	Commission and employed classification and regression tree (C&RT) methodology
2014	Lei et al.	Beijing, China	5-min	Floating car data	0:00 a.m.- 23:59 p.m.	N/A	Maximum likelihood method; Shock wave theory

Year	Author	Location	Data Aggregation	Data Source	Study Periods	TTR Measure(s)	Modeling Algorithm
2016	Zheng et al.	Changsha, China	30s	ANPR data	0:00 a.m.- 23:59 p.m.	Standard deviation, travel time skewness.	Zuylen's delay probability distribution model
2016	Yang	St. Louis, Mo, US	30s	MoDOT TMC monitors	N/A	Standard deviation, Coefficient of variation, Buffer index, Planning time index	General Motors-based travel time estimation model
2017	Wang et al.	Seattle, WA, US	20s	GPS data	5:00 - 11:00 a.m.	Coefficient of variation	Maximum likelihood method; K-Means analysis
2017	Chen et al.	Shanghai, China; Los Angeles, CA, US	N/A	AVI cameras	0:00 a.m.- 23:59 p.m.	Standard deviation, λ^{width}	Copula theory

2.4.2 Network Level TTR Studies

Research studies on modeling TTR at a network level were reviewed and presented in this section. **Error! Reference source not found.** provides a summary of the studies reviewed in this section in chronological order.

2.4.2.1 Yang et al.'s research work

Yang et al. (2014) utilized the Hasofer–Lind–Rackwitz–Fiessler (HL-RF) algorithm which was widely used in the field of reliability engineering to calculate the reliability index of a system. The modeling framework consisted of three parts: travel time estimation, travel time distribution estimation, and corridor-network TTR index calculation. A description of the data set used in this study was followed by the implementation and applications of the proposed method. The results showed that this modeling method could better capture the variability of traffic flow in detail, especially during rush hours.

2.4.2.2 Recker et al.'s research work

Recker et al. (2005) conducted a study on risk-taking route choice via the analyses of travel time variability data of section, corridor, and network under different demand levels. The TTR was also evaluated. In this study, path TTR was defined as "*the probability that the travel time of a given path is within an acceptable threshold.*" OD TTR was defined as "the *probability that the weighted average travel time of a given OD pair is within an acceptable threshold.*" The evaluation procedure was based upon a Monte Carlo simulation framework. Three scenarios were constructed to test how different route choice models affect the estimation of travel time reliability under uncertain environment. The analysis can be concluded as: "*as the degree of risk aversion to network uncertainty increases, travel time also increases and results in lower travel time reliability*."

2.4.2.3 Clark and Watling's research work

Clark and Watling (2005) conducted a study to estimate the total network travel time probability distribution. They considered day-to-day demand variations in the travel demand matrix as a main factor affecting travel time variability and estimated the total travel time density function. The numerical test results indicated that the application of this approach was suitable to understand the impact of capacity changes.

2.4.2.4 Ng and Waller's research work

Ng and Waller (2010) developed a methodology to assess TTR in a transportation network under uncertain road capacities. A Fourier transformation approach was presented to numerically approximate the probability density function (PDF) of the system travel time, where link capacities were assumed to be random and independent. The special case when capacities were normally distributed random variables was also considered. The proposed approach was applied to test networks and analyze the impact of capacity variations on the TTR, which was proved to be valid.

2.4.2.5 Tu et al.'s research work

Tu et al. (2013) investigated a macroscopic TTR diagram to relate the TTR to the network density. The authors conducted empirical analyses to investigate the variability in macroscopic fundamental diagram (MFD) as seen in scatter plots and to show the TTR in relation to the network accumulations using traffic data of freeway networks in Netherlands. A critical TTR accumulation point was found to exist, *''below which network accumulation had little impact on travel time reliability and had a significant impact when it is above''*. The critical TTR accumulation was also found to be usually lower than the critical MFD accumulation.

Table 2.4: Summary of Network Level TTR Studies

Year	Author	Location	Data Aggregation	Data Source	Study Periods	TTR Measure(s)	Modeling Algorithm
2004	Recker et al.	Orange County, CA, US	5-min	Loop detector data	4 - 10 a.m.	Standard deviation	Mixed logit route choice model
2005	Clark and Watling	N/A	N/A	N/A	N/A	100(1 – Pr(M > 5))%	Poisson demand distribution model; Monte Carlo method
2010	Ng and Waller	N/A	N/A	N/A	N/A	Volume-to-capacity ratios	Fourier transforms, BPR function;
2013	Tu et al.	Netherlands	10-min	dual loop detectors	N/A	Probability of traffic breakdown	Piecewise Linear Speed Based (PLSB) trajectory algorithm;
2014	Yang et al.	St. Louis, MO, US	15-min	MoDOT traffic sensors' data	9 a.m.- 5 p.m.	Standard deviation	KDE technique with optimized bandwidths

2.4.3 TTR Studies with the Consideration of Incidents

Research studies on modeling TTR with the consideration of incidents were categorized and reviewed in this section. **Error! Reference source not found.** provides a summary of the studies reviewed in this section in chronological order.

2.4.3.1 Hojati et al.'s research work

Hojati et al. (2016) developed a method to quantify the impact of traffic incidents on TTR on freeways. The authors first obtained the Recurrent Speed Profile (RSP) for each specific link and DOW using the Quantum-Frequency Algorithm. The non-recurrent congestion was identified as an 'event' with a start time and end time. Next, the total travel time due to an event on a set of affected links was modeled, and then the BI was selected as the TTR measure. The authors then conducted a Tobit regression analysis which can handle the presence of censored data either in the lower tail or in the upper tail. Based on the Queensland DOT and STREAMS Incident Management System (SIMS) database, 430 incidents were matched with the identified events. Finally, 3 Tobit model estimation results were shown focusing on crashes, hazards and stationary vehicles.

2.4.3.2 Charlotte et al.'s research work

Charlotte et al. (2017) presented an empirical analysis of travel time distribution on urban roads in the region of Paris, France. Historical data of accidents and roadway works were added to evaluate the impact of some non-recurrent influencing factors. 90th percentile of the travel time distribution was modeled with linear models including explanatory variables including number of lanes, mean value of the travel time distribution, travel direction, time of the day, number of accidents and roadworks.

2.4.4 TTR Studies with the Consideration of Weather Condition

Research studies on modeling TTR with the consideration of weather impacts were categorized in this section. **Error! Reference source not found.** provides a summary of the studies reviewed in this section in chronological order.

2.4.4.1 Martchouk et al.'s research work

Martchouk et al. (2010) studied the travel-time variability with the travel-time data on freeway segments in Indianapolis collected with the help of anonymous Bluetooth sampling techniques. The effects of adverse weather were discussed in the study. The results showed that the travel time increased during adverse weather period, and the variance in travel times during the same time period also increased. Various statistical models were also estimated in the study to understand the effect of individual vehicle travel times variability as well as average travel times variability. For the individual vehicle travel time model, the probability of travel duration time changes of a segment was estimated. As anticipated, higher average speed led to lower individual travel time, whereas higher distance and volume resulted in increased travel time. In the average travel time model, estimated parameter indicated that higher average travel time during the previous time period resulted in higher average travel time during the current period.

2.4.4.2 Peer et al.'s research work

Peer et al. (2012) conducted a study to provide simple rules to predict travel time variability based on the travel time data of 145 (one-directional) highway links in Netherlands. Standard deviation (SD) of travel times was used as the TTR measure. The explanatory variables included DOW, season, weather condition and network condition. Formulas for TTR were built based on 'rough information' and 'fine information'. Mean delay (MD) was also analyzed to express the travel time.

The empirical analysis of travel time variability results showed that *a shorter link is on average associated with lower variability*. The authors also found that variability is positively correlated with the number of lanes for smaller delays and it is negatively correlated with the number of lanes for longer delays.

2.4.4.3 Shao et al.'s research work

Shao et al. (2008) proposed a new travel time reliability-based stochastic user equilibrium traffic assignment model to investigate the effects of rain on risk-taking behaviors of different road users in networks with day-to-day demand fluctuations and variations in travel time. To capture the rain effects on travel time, a new travel time function was developed based on the conventional Bureau of Public Roads (BPR) function. Rain effects on traffic demand were also modeled via the conventional elastic demand function. Finally, it was found in the numerical results that path choice behaviors and traffic demand of different road users were affected by the rainfall intensity.

2.4.4.4 Li et al.'s research work

Li et al. (2016) conducted a study which focused on studying the weather impact on traffic operations. Different rainfall intensity data for every hour of Florida regions were incorporated into the TTR model along with the historical speed database. Different scenarios for each hour (under clear weather, light rain, and heavy rain conditions) were created and applied to the respective roadway sections. The results showed that the speed reductions on arterials were 10% for light rain and 12% for heavy rain. However, the assumed reduction in the speed on arterials caused by rain intensity may need to be verified with additional empirical data during a long period of time to reveal the trends and impacts with more confidence and accuracy.

2.4.4.5 Kamga and Yazici's research work

Kamga and Yazici (2014) conducted a study via merging taxi trips' GPS records and historical weather records of New York City and then calculated the descriptive statistics of travel time for different TOD, DOW and various weather conditions. The weather conditions were categorized into 8 groups including Clear, Light rain, Rain, Heavy rain, Light snow, Snow, Heavy Snow and Unknown. Based on the value of each coefficient, the Classification and Regression Trees (C&RT) model was used to extract the travel time coefficients distribution under each DOW-TOD-Weather category.

The temporal pattern analysis results of each travel time parameter were finally presented. With the analysis results of CV, the authors pointed out: "*Regarding the weather impacts,* *it was found that inclement weather indeed increases average travel times yet decreases variability, resulting in higher travel reliability indicated by lower coefficients of variation*."

Table 2.5: Summary of TTR Studies with the Consideration of Weather/Incident Impacts

Year	Author	Location	Data Aggregation	Data Source	Study Periods	TTR Measure(s)	Modeling Algorithm
2008	Shao et al.	N/A	N/A	N/A	N/A	Standard deviation	RSUE traffic assignment model
2011	Martchouk et al.	Indiana, US	N/A	Microwave detectors	N/A	Standard deviation	Hazards-based model BPR function
2012	Peer et al.	Netherlands	15-min	Loop detector	6:00 a.m. - 8:15 p.m.	Standard deviation	Non-traffic regime-based model; traffic regime-based model
2014	Kamga and Yazici	NYC, US	N/A	Taxis GPS data	N/A	Standard Deviation, Average travel time, Coefficient of variation	Classification and Regression Trees (C&RT) model
2016	Li et al.	Florida	N/A	FDOT database	N/A	Actual travel time	FDOT travel time reliability model
2016	Hojati et al.	Queensland	N/A	Queensland DMTR	N/A	Extra buffer time index	Tobit model
2017	Charlotte et al.	Paris	6-min	Loop detectors	7 - 10 a.m. 5 - 8 p.m. 10p.m. - 5 a.m.	90th percentile travel time	N/A

2.4.5 TTR Studies with the Consideration of Multiple Influencing Factors

Research studies on modeling TTR with the consideration of multiple influencing factors were presented in this section. **Error! Reference source not found.** provides a summary of the studies reviewed in this section in chronological order.

2.4.5.1 Tu's research work

Tu (2008) developed a TTR model with the consideration of four influencing factors including road geometry, adverse weather, speed limits, and traffic accidents. The model was validated using traffic data from urban freeways in Netherlands. The results of road geometry impacts indicated that there was a threshold value L for the length of ramp/weaving section. If the actual length was less than L, the TTR would decrease with the decreasing length of ramp/weaving sections. If the actual length was larger than L, the length has far less impact on travel time reliability. TTR on the freeway was also strongly impacted by the number of ramps per unit road length. Above a threshold value, the more ramps contribute to the lower TTR. The results of adverse weather's impacts indicated that adverse weather conditions clearly have negative effects on TTR on the freeway, which means that travel times are less reliable under adverse weather conditions than those under normal weather conditions, especially at higher inflow levels. The results of speed limit impacts indicated that constant speed limit increases the TTR. However, the effects depended upon the specific constant speed limit value. The results of the whole study indicated that TTR following traffic accidents was lower than that without traffic accidents. In addition, the author concluded that traffic accidents were not the main source of travel time unreliability.

2.4.5.2 Javid and Javid's research work

Javid and Javid (2017) developed a framework to estimate travel time variability caused by traffic incidents based on integrated traffic, road geometry, incident, and weather data. A series of robust regression models were developed based on the data from a stretch in California's highway system. Next, travel time variability was estimated via the proposed speed change models, and the results were compared with the actual changes in travel time. The results of the split-sample validation showed the effectiveness of the proposed models in estimating the travel time variability. In conclusion, for incidents occurring on weekends, the highway clearance time would be shorter. Shoulder existence and lane width would adversely impact downstream highway clearance time.

2.4.5.3 Florida Department of Transportation's research work

Florida DOT (2011) developed a methodology to estimate TTR with the consideration of a set of different possible scenarios. Expected travel times were calculated for those scenarios along with the probability of occurrence of each scenario. The concept was illustrated in Figure 2.1 below in which each analysis period during each day belongs to a particular scenario. A scenario was a set of conditions affecting the travel time of the sections, including non-congested vs. congested, weather, incidents, and work zones. All days or analysis periods with the same set of conditions were categorized under a given scenario. The percent of analysis periods or days that operate under a scenario constituted the probability of occurrence. The methodology developed estimated expected travel time for each of the scenarios identified, along with the expected frequency of occurrence. The method then assembled estimated travel times along with their respective frequencies and obtained travel time distribution for the subject section.

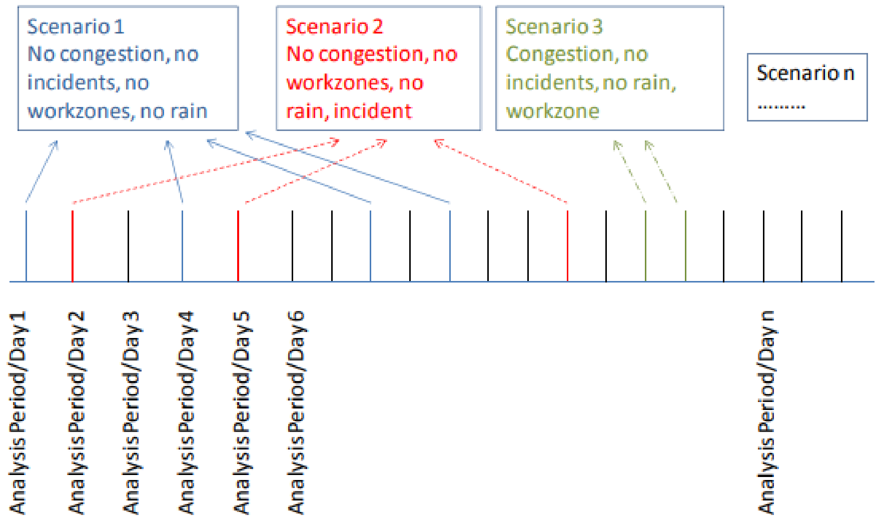

Figure 2.1: Florida DOT Scenario Selection Method
Source: Florida DOT (2011)

2.4.5.4 Schroeder et al.'s research work

Schroeder et al. (2013) presented a methodology for freeway reliability analysis based on freeway data in North Carolina. The variability impact considerations included time-of-day, day-of-week, and month-of-year differences, and various nonrecurring congestion sources (such as weather, incidents, work zones, and special events). The freeway scenario generator (FSG) was used and resulted in 2,508 scenarios based on freeway facility data in North Carolina. The resulting travel time distribution was presented, and a sensitivity analysis was conducted to explore the relationship between weather and incidents and the overall reliability of the facility.

2.4.5.5 Barkley et al.'s research work

Barkley et al. (2012) pointed out that although current research have suggested that bimodal normal distribution models can provide insight into the TTR within the free-flow and congested states that most facilities experience. However, depending on the frequency and severity of non-recurrent congestion, two states may not sufficiently capture a facility's true operational variability. To address this issue, this study presented a methodology for determining the optimal number of travel time states using statistical goodness-of-fit tests and for ensuring that the results meaningfully explain travel time variability. More specifically, the Bayesian information criterion (BIC) was leveraged to compare the model fits for normal distributions composed of one to nine states. To examine the relationship between non-recurrent congestion and travel time state, data on local sources of non-recurrent congestion were collected. Travel times that coincided with non-recurrent congestion instances were manually tagged with the condition during their measurement:

(a) baseline, (b) incident, (c) weather, (d) special event, (e) lane closure, or (f) high demand. This study utilized travel times generated from loop detectors at a 5-min aggregation, which were obtained from the Caltrans Performance Measurement System (PeMS). The results suggested that multistate models when combined with data on non-recurrent congestion could inform the relationship between specific types of non-recurrent congestion and the travel time state. This valuable information could help agencies develop targeted congestion mitigation measures to improve TTR.

2.4.5.6 Kwon et al.'s research work

Kwon et al. (2017) developed an empirical corridor level method to study the TTR. The authors divided the variables which had an impact on the travel time into three categories: traffic influencing events (traffic incidents and crashes, work zone activity, weather and environmental conditions), traffic demand (fluctuations in day-to-day demand and special events), and physical road features (traffic control devices and inadequate base capacity). A linear regression statistical model was then constructed to conduct the travel time reliability analysis. Buffer time (95^{th} percentile of travel time - median travel time) was chosen over other measures to represent the TTR because it was more popular and easier to formulate and fit the model. The model was tested in San Francisco Bay Area and used to identify how each variable contributes to the TTR. The results of this study provided useful insights into predicting the TTR.

2.4.5.7 Kim's research work

Kim (2014) conducted a study on TTR and developed a compound Gamma distribution model. The model captured both vehicle-to-vehicle (V2V) and day-to-day (D2D) travel delay. The author also proposed a framework that features scenario-based simulation approaches. The approach aimed to capture different unreliability factors such as incidents, bad weather, work-zone and planned special events through several scenarios and analyze their impacts on travel time outcomes using dynamic traffic assignment (DTA) models. This approach could provide the ability to forecast potential variations in travel time and estimate of population travel time distributions with more accuracy.

Table 2.6: Summary of TTR Studies with the Consideration of Multiple Influencing Factors

Year	Author	Location	Data Aggregation	Data Source	Study Periods	TTR Measure(s)	Modeling Algorithm
2008	Tu	Delft, Netherlands	N/A	Regiolab-Delft monitoring system.	N/A	λ^{skew}, λ^{width}	Dynamic Traffic Assignment
2011	Florida DOT	Florida, US	N/A	FDOT database	4-7 p.m.	Planning time index	Scenario based method
2012	Barkley et al.	San Diego, CA, US	5-min	PeMS	N/A	Standard deviation	Multistate model; Expectation-maximization algorithm
2013	Schroeder et al.	Durham, NC, US	15-min	INRIX	2-8 p.m.	Travel time index	FREEVAL HCM model
2014	Kim	NYC, US	5-min	ASOS station, INFORM system	6-10 a.m.	Percent variation, Misery index and Buffer time index	Expectation-maximization algorithm
2017	Kwon et al.	San Francisco, CA, US	N/A	PeMS	7 - 9 a.m. 11 a.m. - 1 p.m. 4-6 p.m.	Buffer time	FDOT travel time reliability model
2017	Javid and Javid	California, US	5-min	PEOS database	N/A	Index of agreement, Correlation coefficient	Robust regression

2.5 Summary

A comprehensive review and synthesis of the current and historical researches related to TTR definitions, measures, analysis and modeling methodologies have been discussed and presented in the preceding sections. This is intended to provide a solid reference and assistance in developing TTR models for future tasks.

Chapter 3. Data Collection and Processing

3.1 Introduction

This chapter provides the basic information needed to analyze TTR, including the travel time data and historical weather data utilized in this study. The following sections are organized as follows. Section 3.2 presents detailed information about the raw travel time data source, followed by the discussions about weather data collection in section 3.3. Section 3.4 described details of data processing. Finally, section 3.5 concludes this chapter with a summary.

3.2 Travel Time Data Collection

The TTR index is measured based on the distribution of travel time on a segment over time. Effective calculation of this index requires accurate, high-quality data. This study focuses on the travel time data gathered from the Regional Integrated Transportation Information System (RITIS) website and use the collected data to conduct the TTR analysis. A series of major freeway segments are selected for the case study: Interstate 77 (I-77) Southbound (Figure 3.1) is one of the most heavily traveled Interstate highways in Charlotte area and runs from north to south. All the selected segments have uninterrupted coverage of RITIS data 24 hours per day and 365 days a year.

Interstate 77 begins at the South Carolina state line, near Fort Mill, and goes through the city of Charlotte as a major north-south corridor, connecting the Charlotte center area with the suburbs of Pineville, Huntersville, Cornelius, and Davidson. The highways in Charlotte area experience massive traffic congestion during weekdays due to heavy commuter and interstate traffic.

The selected section of I-77 Southbound starts from the intersection with Harris oak Blvd and ends at the interchange with I-485 (Exit 2) at the south part of the city. 32 roadway segments are selected in this study, and the total length of the selected section is 19 miles.

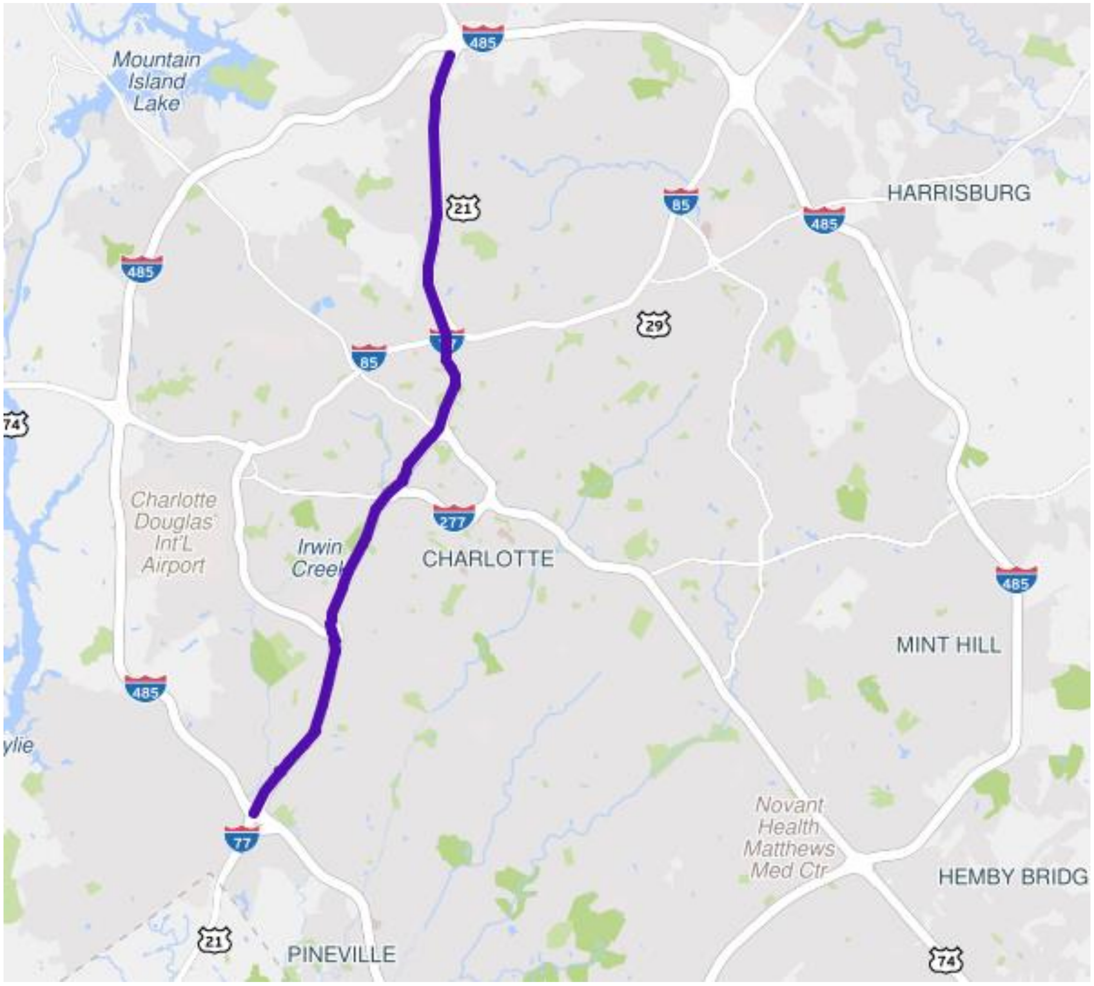

Figure 3.1: Selected I-77 Southbound Section

In order to evaluate TTR, there is a need for accurate travel time data. As discussed in the literature review, in the past, travel time was deduced from the loop detector data, historical trends or floating car runs. In this study, travel time and speed data are obtained from the RITIS website which gathered information about roadway speeds and vehicle counts from 300 million real-time anonymous mobile phones, connected cars, trucks, delivery vans, and other fleet vehicles equipped with GPS locator devices.

On the RITIS website probe data analytic suite, the raw probe data can be downloaded with the desired section and format. The roadway section can be selected based on the Road states and countries, TMCs, Directions, Zip codes, Road class and Road name. The partial sections can be selected with the selection of begin and end intersections. The date range can be selected from January 1st, 2008 to today. Seven days of week and times of day from 12:00 AM to 11:59 PM can also be selected. The units of travel time can be categorized into both seconds and minutes. The averaging period can be selected as five minutes, ten minutes, fifteen minutes and one hour. A sample of raw travel time data utilized in this study is shown in Table 3.1 below:

Table 3.1: Sample Raw Travel Time Data

TMC Code	Measurement_tstamp	Speed	Travel_time_seconds
125N04784	1/1/2015 0:00	62.91	53.58
125N04783	1/1/2015 0:00	61.17	12.82
125N04786	1/1/2015 0:00	60.43	47.56
125N04785	1/1/2015 0:00	61.3	11.85
125N04780	1/1/2015 0:00	63.97	14.59
125N04782	1/1/2015 0:00	63.04	21.73
125N04781	1/1/2015 0:00	62.79	12.42
125N04788	1/1/2015 0:00	65.03	29.6
125N04787	1/1/2015 0:00	63.5	53.76
125N04789	1/1/2015 0:00	64.79	54.5
125-04783	1/1/2015 0:00	62.98	33.22
125-04782	1/1/2015 0:00	62.75	35.68
125-04785	1/1/2015 0:00	60.54	5.16
125N04784	1/1/2015 0:00	62.91	53.58

Table 3.1 contains the following information:

TMC_Code: The RITIS Probe Data Analytics Suite uses the TMC (traffic message channel) standard to uniquely identify each road segment. This field indicates the segment ID.

Measurement_tstamp: This field indicates the timestamp of the record.

Speed: This field indicates the current estimated harmonic mean speed for the roadway segment in miles per hour.

Travel_time_seconds: This field indicates the time it will take to drive along the roadway segment.

3.3 Weather Data Collection

The historical weather data near the Charlotte Douglas International airport can be found at the www.wunderground.com website. The raw weather data can be achieved within the desired time period. The date range can be selected from January 1st, 1941 to today.

The raw weather data include information on different categories such as temperature, dew point, humidity, pressure, visibility, wind direction, wind speed, gust speed, precipitation, and conditions. The raw weather data from this website were recorded per hour. Due to the discrepancy in the time interval, one-to-one mapping or correlation study cannot be done using the original data. Hence, the methodology to combine the traffic data with the weather data will be discussed in the next section. The sample of weather data achieved is shown in Table 3.2 below.

Table 3.2: Sample Raw Weather Data

Date	Time (EDT)	Visibility	Conditions
Saturday, March 14, 2009	6:55 AM	**2.0** mi	Rain
Saturday, March 14, 2009	7:55 AM	**2.0** mi	Rain
Saturday, March 14, 2009	8:55 AM	**2.0** mi	Light Rain
Saturday, March 14, 2009	9:55 AM	**2.0** mi	Light Rain
Saturday, March 14, 2009	10:55 AM	**3.0** mi	Light Rain
Saturday, March 14, 2009	11:55 AM	**2.0** mi	Light Rain
Saturday, March 14, 2009	12:55 PM	**3.0** mi	Light Rain
Saturday, March 14, 2009	1:55 PM	**7.0** mi	Light Rain
Saturday, March 14, 2009	2:55 PM	**6.0** mi	Light Rain
Saturday, March 14, 2009	3:55 PM	**7.0** mi	Light Rain
Saturday, March 14, 2009	4:55 PM	**4.0** mi	Rain

3.4 Data Processing

Based on previous studies, it is widely accepted that only severe weather events will cause a significant impact on speeds and travel times. Due to the weather characteristics in the Charlotte area and the distribution of each weather category, detailed weather conditions are categorized into three groups including normal, rain, and snow/fog/ice. Table 3.3 presents the detailed classification of the weather conditions. Conditions such as “overcast” or “mostly cloudy” are assumed to be no different from “clear” conditions due to no obvious impact on traffic conditions. These conditions are categorized into ‘normal’. All the conditions such as ‘rain’ or ‘thunderstorm’ are categorized as ‘rain’. In order to ensure the acceptable sample size, “snow”, “fog”, “ice pellet”, and other similar conditions are combined together due to their rate of occurrence.

Table 3.3: Classification of the Weather Conditions

Original Weather Condition	New Weather Category
Haze	Snow/fog/ice
Fog	
Smoke	
Patches of Fog	
Mist	
Shallow Fog	

Original Weather Condition	New Weather Category
Light Freezing R	
Light Ice Pellet	
Light Freezing D	
Light Freezing F	
Ice Pellets	
Light Snow	
Snow	
Heavy Snow	
Clear	Normal
Partly Cloudy	
Mostly Cloudy	
Scattered Clouds	
Overcast	
Unknown	
Squalls	
Light Rain	Rain
Rain	
Heavy Rain	
Light Drizzle	
Heavy Thunderstorm	
Thunderstorms an	
Light Thunderstorm	
Thunderstorm	
Drizzle	

Figure 3.2 illustrates the data processing steps. In order to merge the link travel times dataset with historical weather dataset, the issue of different intervals of two datasets should be resolved first. The RITIS datasets are aggregated into 15-minute intervals, while the weather dataset is aggregated into one-hour intervals. Therefore, the weather conditions are distributed evenly with RITIS dataset based on the timestamp. Based on previous studies, different DOWs were usually categorized as weekdays and weekends. Therefore, the DOW variables are classified as weekdays and weekends categories.

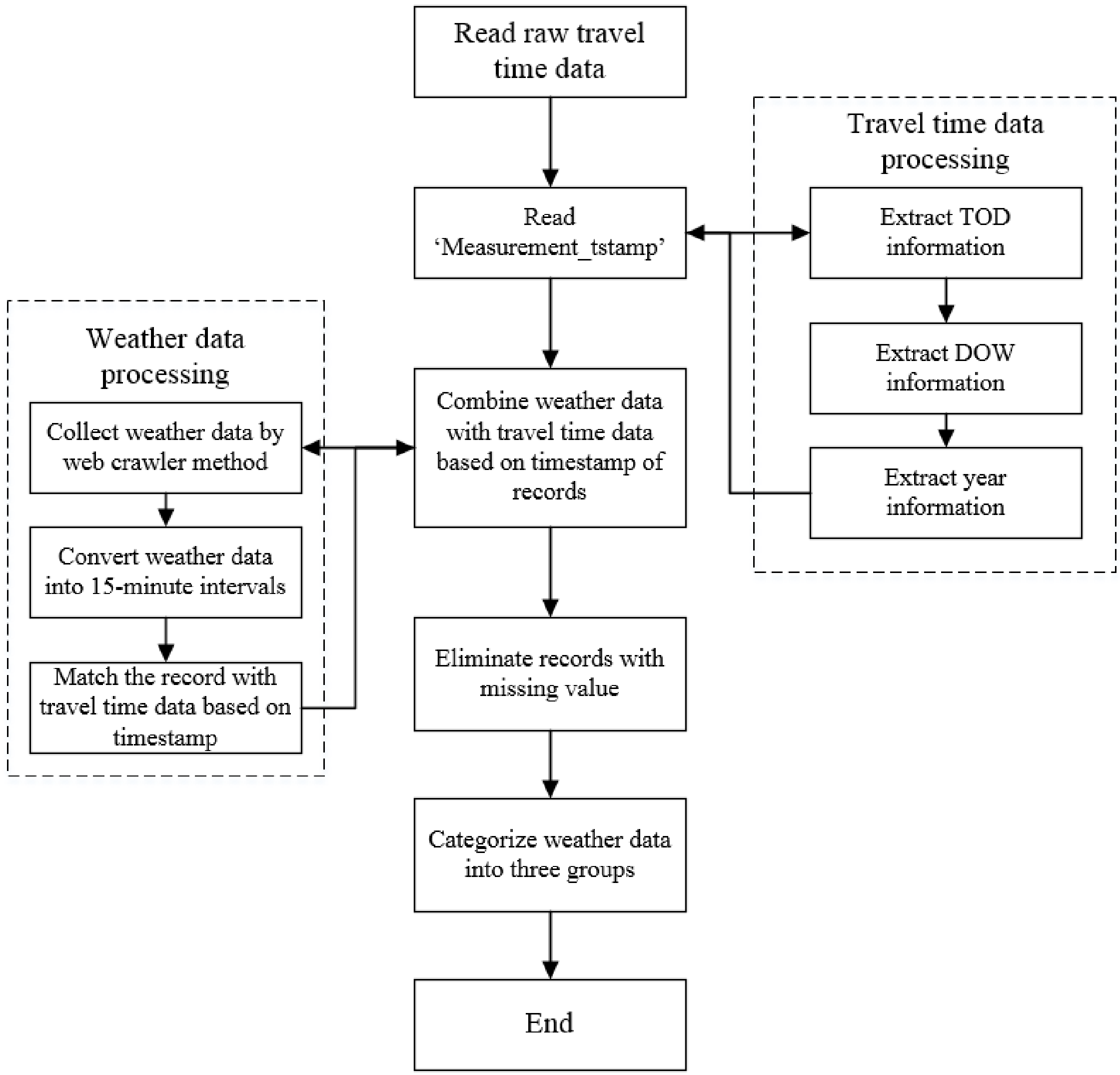

Figure 3.2: Data processing flowchart

3.5 Summary

This chapter presents the detailed information on the data source, data structure, and processing methodology to combine the travel time with raw weather data. This is intended to provide a solid reference and assistance in analyzing travel time reliability for future tasks.

Chapter 4. TTR Variability Analysis

4.1 Introduction

The chapter presents the analysis of TTR variability patterns. The following sections are organized as follows. Section 4.2 shows the study location identification process based on the TTR. Section 4.3 presents the TTR variability patterns under all conditions. Section 4.4 discusses the TTR variability patterns considering the DOW. Section 4.5 describes the TTR variability patterns considering different weather conditions. Finally, section 4.6 concludes this chapter with a summary.

4.2 Study Location Identification Based on TTR

This section describes how to identify study locations based on the TTR measure. The indicator is calculated by aggregating the speed and travel time observations collected during the time interval of interest across a year. A number of performance measures such as FOC, PTI, BI can be applied to achieve this goal. For illustration purpose and other reasons that will be discussed later, we only present how to extract the PTI values for each segment during each time interval.

4.2.1 Selection of TTR Measures

TTR measures have been increasingly encouraged by FHWA for use to manage and operate transportation systems. Previous research has led to the employment of various TTR measures to assist in highway performance evaluation and congestion management. In the literature review chapter, we have introduced different types of travel time reliability measures such as the 95th percentile travel time, buffer index (BI), planning time index (PTI), misery index (MI), coefficient of variation (CV), frequency of congestion (FOC), skew of travel time distribution and width of travel time distribution.

There are four most widely used TTR measures in previous studies and they are BI, PTI, CV, and FOC. However, BTI and CV have the limitation since their values depend on the average travel time, which may change over time (Fan and Gong, 2017). Therefore, the PTI is chosen as the primary measure of travel time reliability in this study. It is calculated by dividing 95th percentile travel time by the free flow travel time so as to represent the percentage of extra travel time that most people will need to add on to their trip in order to ensure on-time arrival. For example, a PTI value of 1.5 at 5 PM means that for a 20-minute trip in light traffic, 30 minutes should be planned at 5 PM to make sure that he or she is on time. The equation of PTI is provided below:

$$PTI_i = \frac{T_{i95}}{FFTT_i}$$

Where

PTI_i = The planning time index of segment *i*.

T_{i95} = 95th percentile travel time on the TMC segment i during the study period across multiple days (e.g., a month) or a year.

$FFTT_i$ = Free-flow travel time on TMC i during the same observation period as mentioned above.

For each roadway segment, the free-flow travel time is computed by dividing the length of segment by the free-flow speed, which was defined as the 85th percentile speed during overnight hours (10 p.m. to 5 a.m.) (Florida DOT, 2011, Schrank et al. 2015, Fan and Gong, 2017).

4.2.2 Corridor PTI Information Aggregation

The first step to identify the study segments is to plot the two-dimensional PTI matrix for each road segment along the corridor. This would provide a straightforward and visualized tool for decision-makers to grasp the average traffic conditions along a corridor. The long-term (in one-year period) PTI values of each segment from 2011 to 2015 were calculated and shown in Figure 4.1 to Figure 4.5, respectively. Note that in these figures, the horizontal axis denotes the time of day and the vertical axis represents TMC segments along the selected section on I-77 Southbound. Each cell represents the PTI value. The darker the color, the higher the PTI.

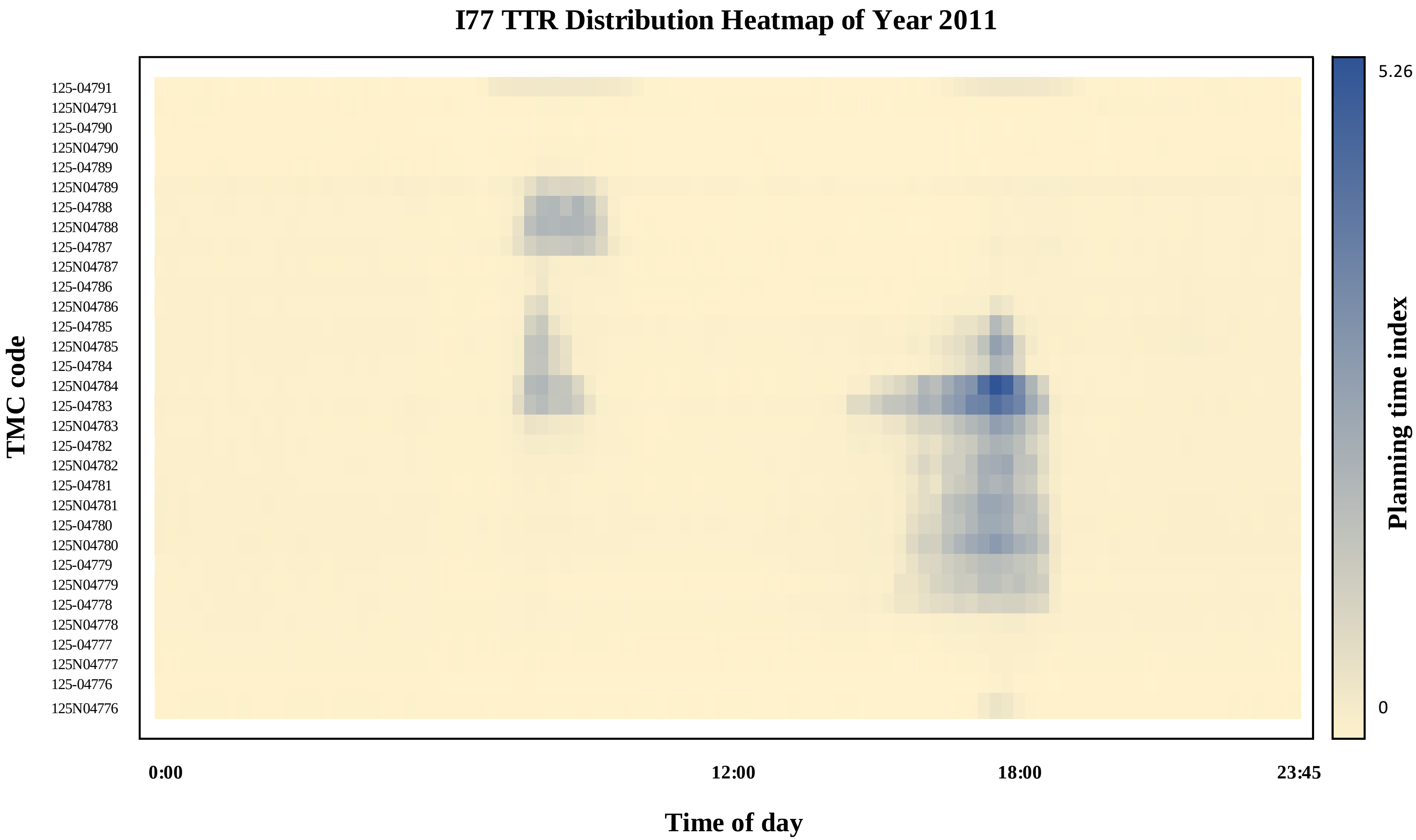

Figure 4.1: PTI Heatmap of I77 (SB) in Year 2011

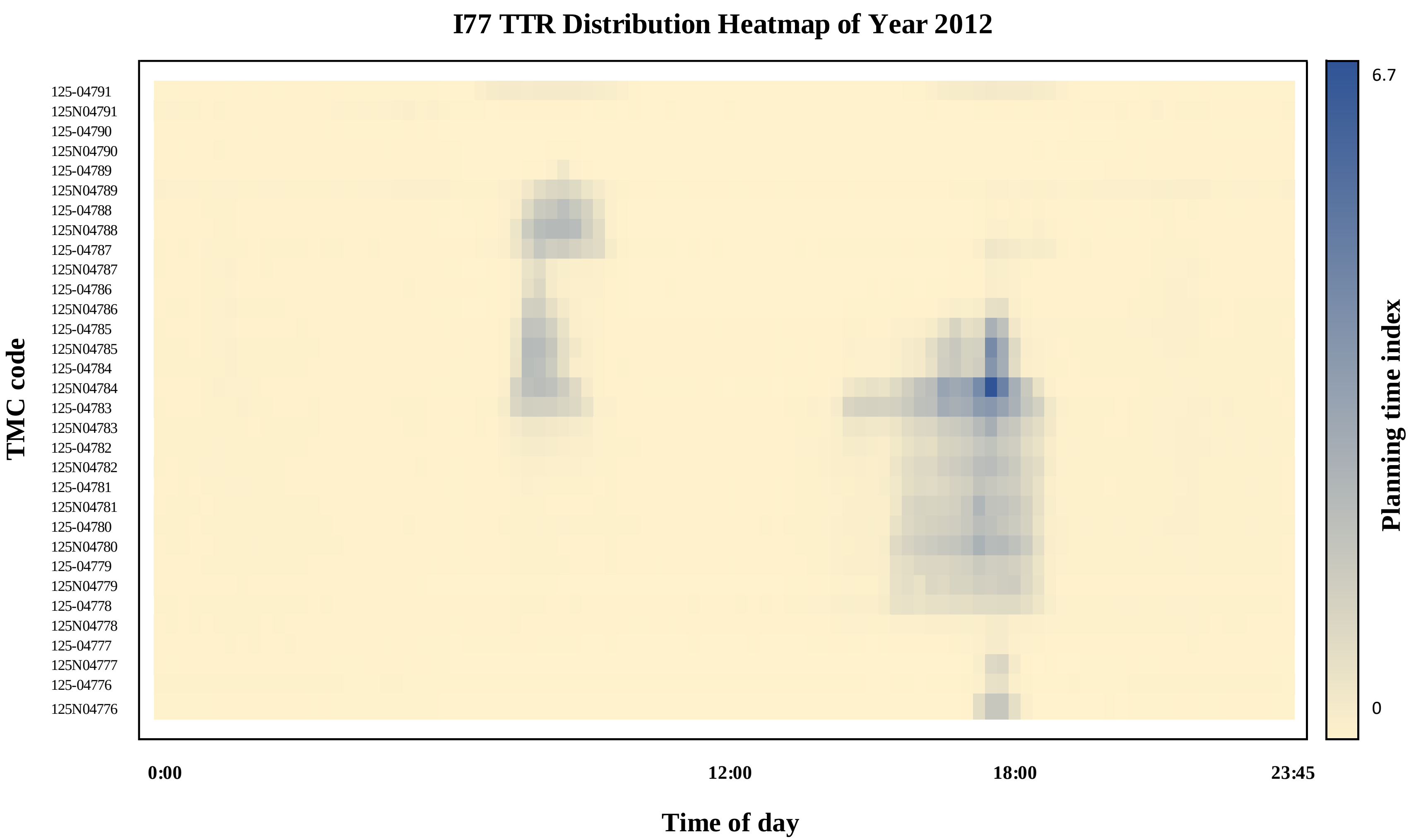

Figure 4.2: PTI Heatmap of I77 (SB) in Year 2012

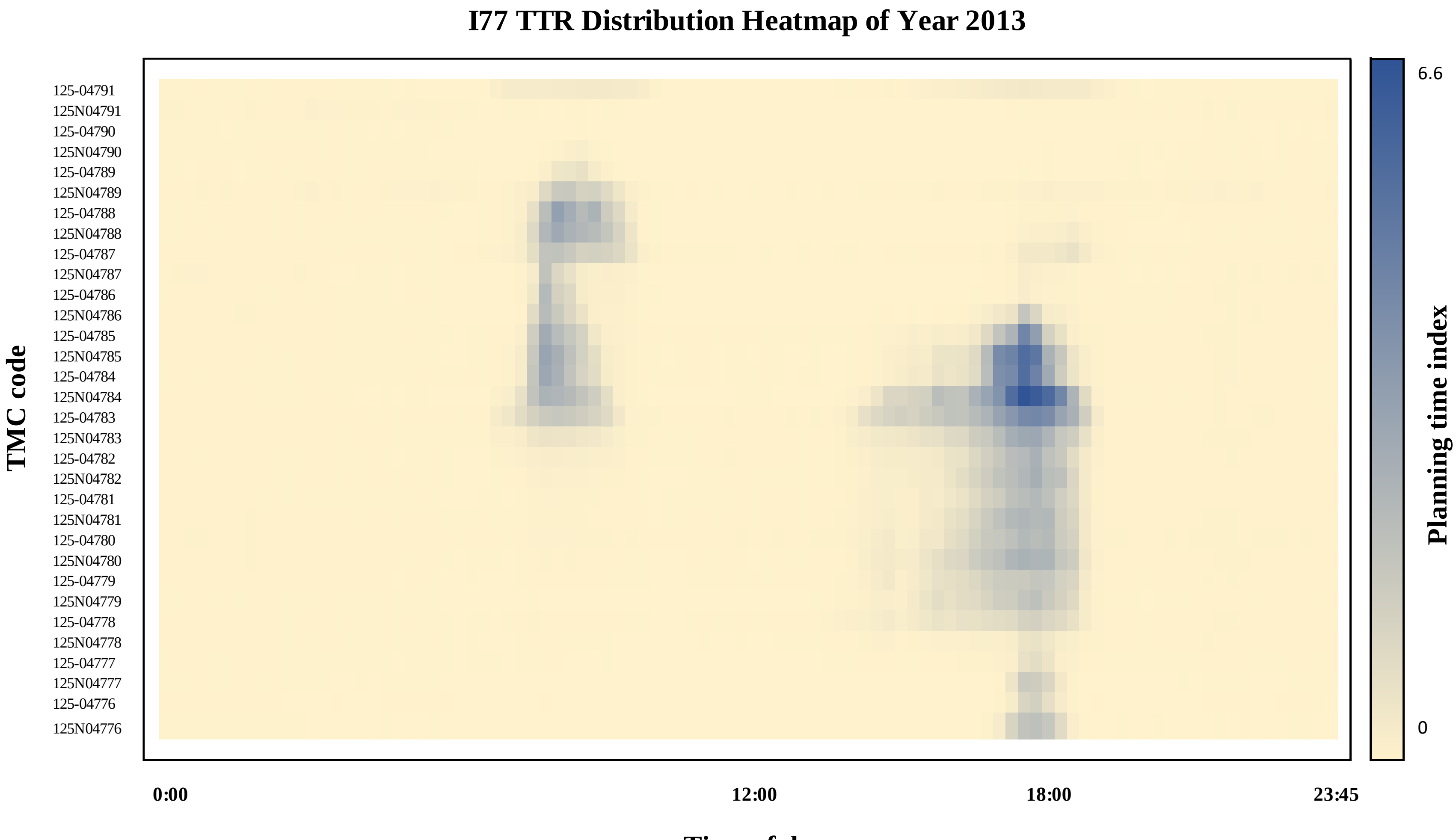

Figure 4.3: PTI Heatmap of I77 (SB) in Year 2013

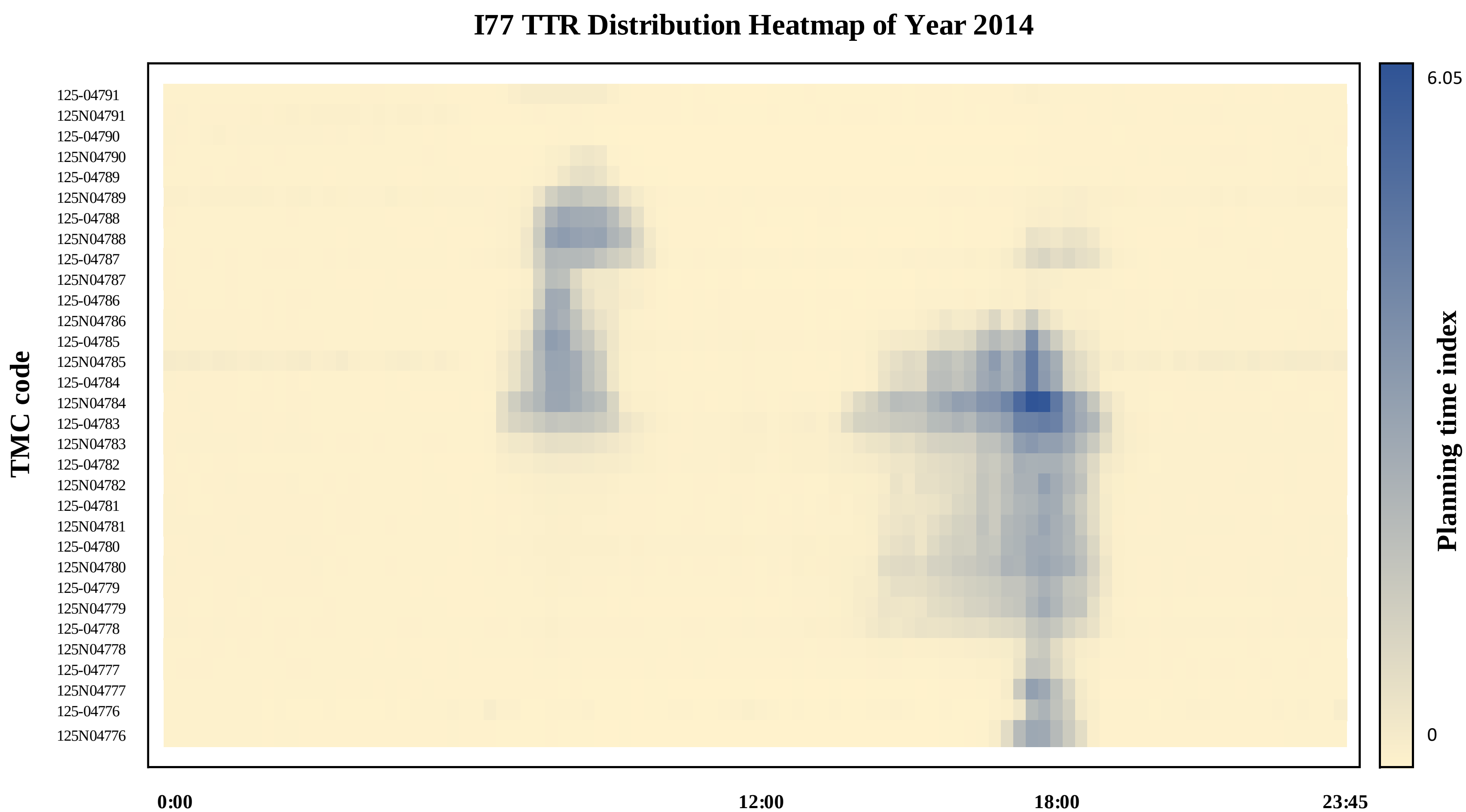

Figure 4.4: PTI Heatmap of I77 (SB) in Year 2014

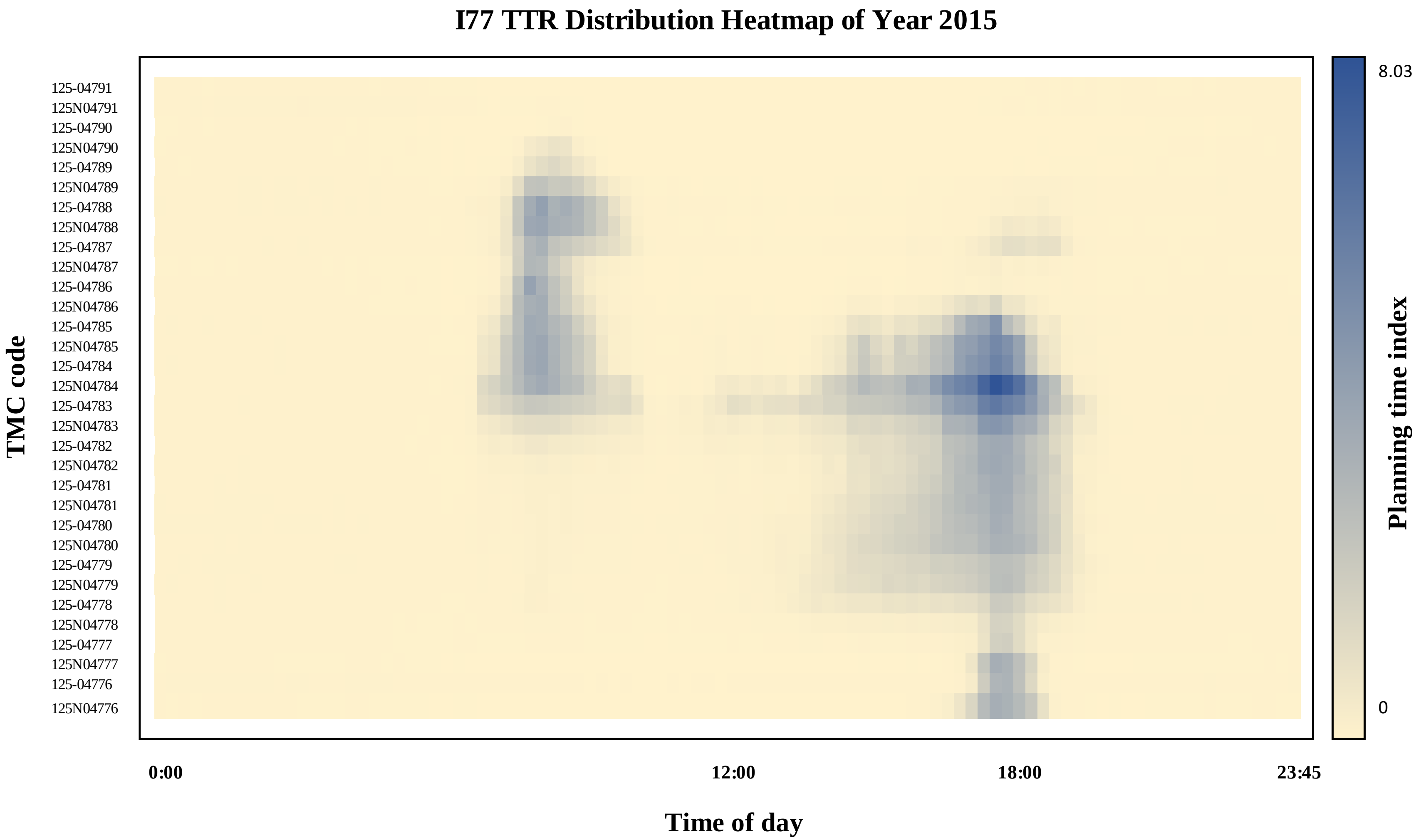

Figure 4.5: PTI Heatmap of I77 (SB) in Year 2015

The PTI heatmaps show that, during morning peak periods, traffic congestion generally occurs in the vicinity of segment 125N04783 to segment 125N04789; during evening peak periods, drivers routinely experience frequent congestion between segment 125N04776 and segment 125N04785. The study location identification criteria will be discussed in the next section.

4.2.3 Study Location Identification Based on PTI Rating

In order to select the sections which can represent different traffic conditions, the qualitative ratings for each freeway segment in the study area are conducted and further classified into different categories/levels based on the qualitative criteria of a previous study (Wolniak and Mahapatra, 2014). The ratings which are given based on the PTI values are: (1) reliable (PTI<1.5); (2) moderately to heavily unreliable (1.5<PTI<2.5) and (3) extremely unreliable (PTI>2.5).

Based on the rating criteria mentioned above, eight segments (shown in Figure 4.6) which contain the four PTI rating cases are selected as the sample study segments. The four cases are:

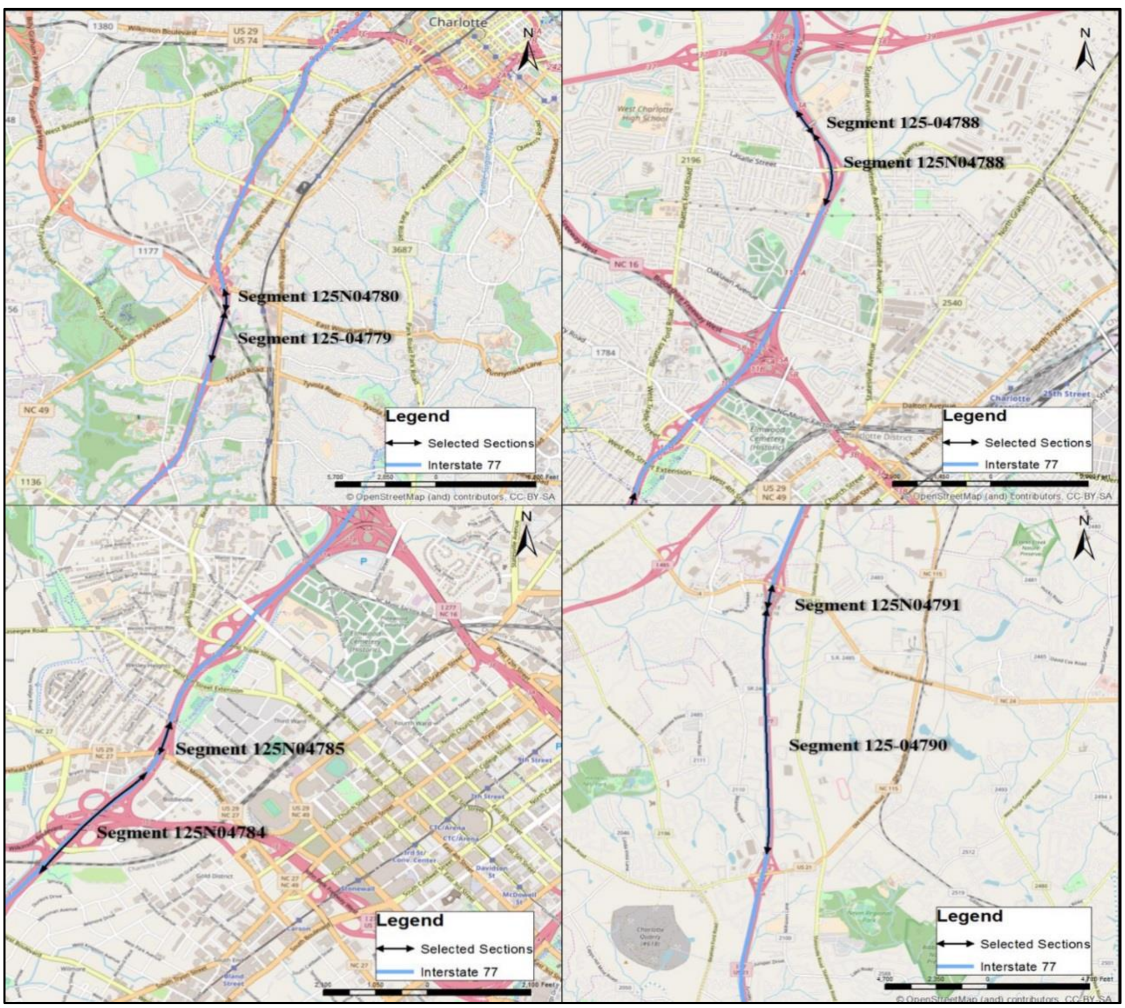

Figure 4.6: Location of Selected Segments

Case 1 (PM peak only): The average PTI during AM peak period is reliable and during PM peak period is unreliable/extremely unreliable. The selected segments are 125-04779 and 125N04780.

Case 2 (AM peak only): The average PTI during AM peak period is unreliable/ extremely unreliable and during PM peak period is reliable. The selected segments are 125N04788 and 125-04788.

Case 3 (Double peak): The average PTI during both AM and PM peak periods are unreliable/ extremely unreliable. The selected segments are 125N04784 and 125N04785.

Case 4 (No peak): The average PTI during both AM and PM peak periods are reliable. The selected segments are 125-04790 and 125N04791.

Table 4.1 below describes the detailed information about the TMC code, segment location, segment length, year, average PTI and rating of these selected segments. The information on all the segments in the study area can be found in Appendix A.

Table 4.1: **PTI ratings during AM and PM peak periods of selected segments**

TMC Code	Segment Location	Segment Length (miles)	Year	Time Period	Average PTI	Rating
125-04779	TYVOLA RD/EXIT 5	0.67	2011	AM Peak	1.09	reliable
				PM Peak	2.00	unreliable
			2012	AM Peak	1.07	reliable
				PM Peak	1.98	unreliable
			2013	AM Peak	1.06	reliable
				PM Peak	2.08	unreliable
			2014	AM Peak	1.09	reliable
				PM Peak	2.34	unreliable
			2015	AM Peak	1.11	reliable
				PM Peak	2.70	extremely unreliable
			Average	AM Peak	1.08	reliable
				PM Peak	2.22	unreliable
125N04780	WOODLAWN RD/EXIT 6	0.26	2011	AM Peak	1.10	reliable
				PM Peak	2.45	unreliable
			2012	AM Peak	1.07	reliable
				PM Peak	2.43	unreliable
			2013	AM Peak	1.06	reliable
				PM Peak	2.49	unreliable
			2014	AM Peak	1.10	reliable
				PM Peak	2.69	extremely unreliable
			2015	AM Peak	1.12	reliable

TMC Code	Segment Location	Segment Length (miles)	Year	Time Period	Average PTI	Rating
				PM Peak	3.19	extremely unreliable
			Average	AM Peak	1.09	reliable
				PM Peak	2.65	extremely unreliable
125N04784	I-277/US-74/EXIT 9	0.94	2011	AM Peak	1.60	unreliable
				PM Peak	3.10	extremely unreliable
			2012	AM Peak	1.75	unreliable
				PM Peak	3.34	extremely unreliable
			2013	AM Peak	2.01	unreliable
				PM Peak	4.04	extremely unreliable
			2014	AM Peak	2.33	unreliable
				PM Peak	4.09	extremely unreliable
			2015	AM Peak	2.77	extremely unreliable
				PM Peak	5.45	extremely unreliable
			Average	AM Peak	2.09	unreliable
				PM Peak	4.00	extremely unreliable
125N04785	US-29/NC-27/MOREHEAD ST/EXIT 10	0.20	2011	AM Peak	1.38	reliable
				PM Peak	1.71	unreliable
			2012	AM Peak	1.60	unreliable
				PM Peak	2.08	unreliable
			2013	AM Peak	1.87	unreliable
				PM Peak	2.95	extremely unreliable
			2014	AM Peak	2.11	unreliable
				PM Peak	2.85	extremely unreliable
			2015	AM Peak	2.63	extremely unreliable
				PM Peak	3.61	extremely unreliable
			Average	AM Peak	1.92	unreliable
				PM Peak	2.64	extremely unreliable
125N04788	LASALLE ST/EXIT 12	0.53	2011	AM Peak	1.81	unreliable
				PM Peak	1.08	reliable
			2012	AM Peak	1.90	unreliable
				PM Peak	1.07	reliable

TMC Code	Segment Location	Segment Length (miles)	Year	Time Period	Average PTI	Rating
			2013	AM Peak	2.09	unreliable
				PM Peak	1.11	reliable
			2014	AM Peak	2.32	unreliable
				PM Peak	1.26	reliable
			2015	AM Peak	2.62	extremely unreliable
				PM Peak	1.25	reliable
			Average	AM Peak	2.15	unreliable
				PM Peak	1.16	reliable
125-04788	LASALLE ST/EXIT 12	0.11	2011	AM Peak	1.72	unreliable
				PM Peak	1.09	reliable
			2012	AM Peak	1.71	unreliable
				PM Peak	1.06	reliable
			2013	AM Peak	2.09	unreliable
				PM Peak	1.07	reliable
			2014	AM Peak	2.14	unreliable
				PM Peak	1.11	reliable
			2015	AM Peak	2.63	extremely unreliable
				PM Peak	1.13	reliable
			Average	AM Peak	2.06	unreliable
				PM Peak	1.09	reliable
125-04790	US-21/SUNSET RD/EXIT 16	2.25	2011	AM Peak	1.05	reliable
				PM Peak	1.05	reliable
			2012	AM Peak	1.04	reliable
				PM Peak	1.04	reliable
			2013	AM Peak	1.04	reliable
				PM Peak	1.04	reliable
			2014	AM Peak	1.06	reliable
				PM Peak	1.05	reliable
			2015	AM Peak	1.07	reliable
				PM Peak	1.05	reliable
			Average	AM Peak	1.07	reliable
				PM Peak	1.07	reliable
125N04791	HARRIS OAK BLVD/REAMES RD/EXIT 18	0.62	2011	AM Peak	1.06	reliable
				PM Peak	1.05	reliable
			2012	AM Peak	1.05	reliable
				PM Peak	1.05	reliable
			2013	AM Peak	1.07	reliable

TMC Code	Segment Location	Segment Length (miles)	Year	Time Period	Average PTI	Rating
				PM Peak	1.06	reliable
			2014	AM Peak	1.07	reliable
				PM Peak	1.07	reliable
			2015	AM Peak	1.05	reliable
				PM Peak	1.05	reliable
			Average	AM Peak	1.04	reliable
				PM Peak	1.04	reliable

4.3 TTR Variability Patterns at Study Locations

4.3.1 TTR Variability Pattern under Case 1

The PTIs of segment 125-04779 and 125N04780 from 2011 to 2015 are shown in Figure 4.7 and 4.8. These two sections are located at the south part of the Charlotte downtown area. The volume of outbound traffic during PM hours is high and therefore contributes to the frequent congestion under PM peak condition. In more detail, in the year 2015, these two segments had obvious higher PTI values during peak hours than those in the years of 2011-2014. The condition like this may be attributed to different factors such as the traffic volume, weather condition and accidents. Based on the historical weather data, the frequency of adverse weather in the year 2015 is higher than that in the year from 2011 to 2014. In order to eliminate the possible influence of adverse weather, the TTR distribution under only normal conditions during each year are also tested and the average daily PTI of 2015 is reduced a little bit (from 2.1 to 2.0) but still higher than PTIs of year 2011-2014. With respect to traffic accident, no detailed historical crash information about I77 is found. However, the number of total crashes in Mecklenburg county in each year had been getting higher and higher from 2011 to 2015 (15476, 15915, 16790, 19847, and 21096, respectively) (NCDMV, 2016). This can also be another potential reason that contributes to the worsening of the traffic condition in the year 2015.

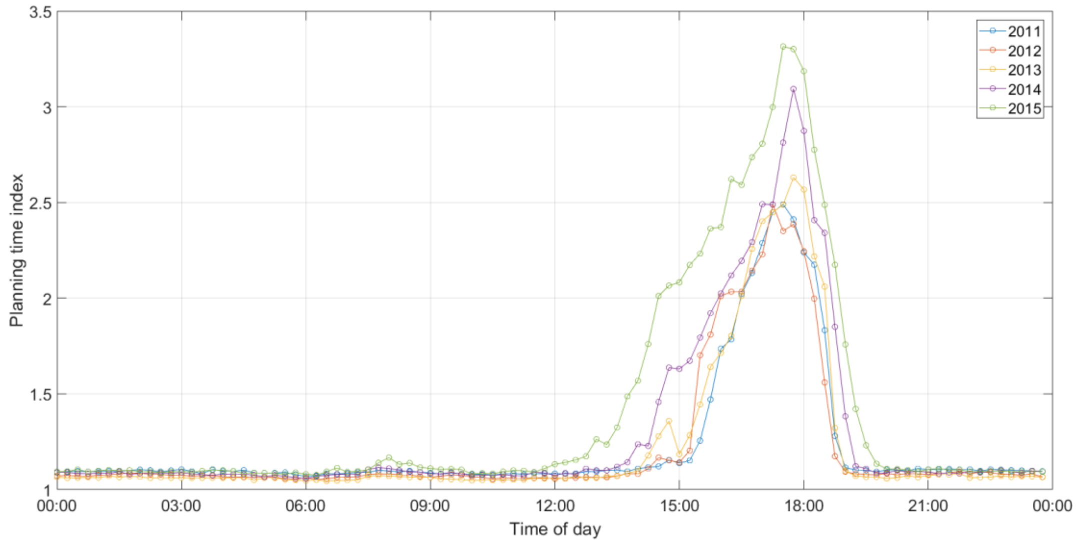

Figure 4.7: TTR Variability Pattern of Segment 125-04779 in 5 Years

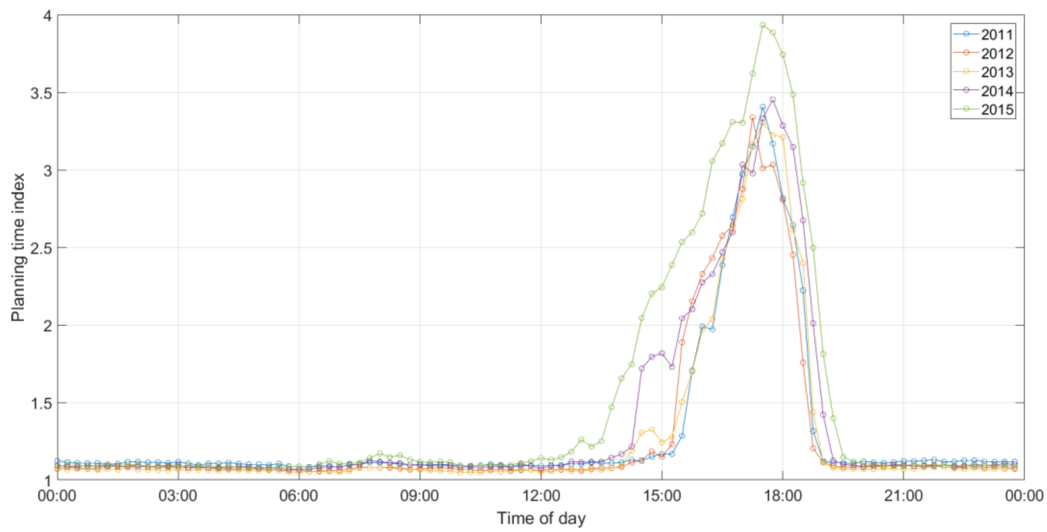

Figure 4.8: TTR Variability Pattern of Segment 125N04780 in 5 Years

4.3.2 TTR Variability Pattern under Case 2

The PTIs of segment 125N04788 and 125-04788 from 2011 to 2015 are shown in Figure 4.9 and 4.10. These two sections are located at the north part of the Charlotte downtown area. The volume of inbound traffic during AM hours is high and therefore contributes to the frequent congestion under AM peak condition. Similar to case 1, in the year 2015, these two segments had obvious higher PTI values during peak hours than that of years of 2011-2014. The condition like this may also be explained by the potential reason like adverse weather and accident that contribute to the worsening of the traffic condition in the year 2015.

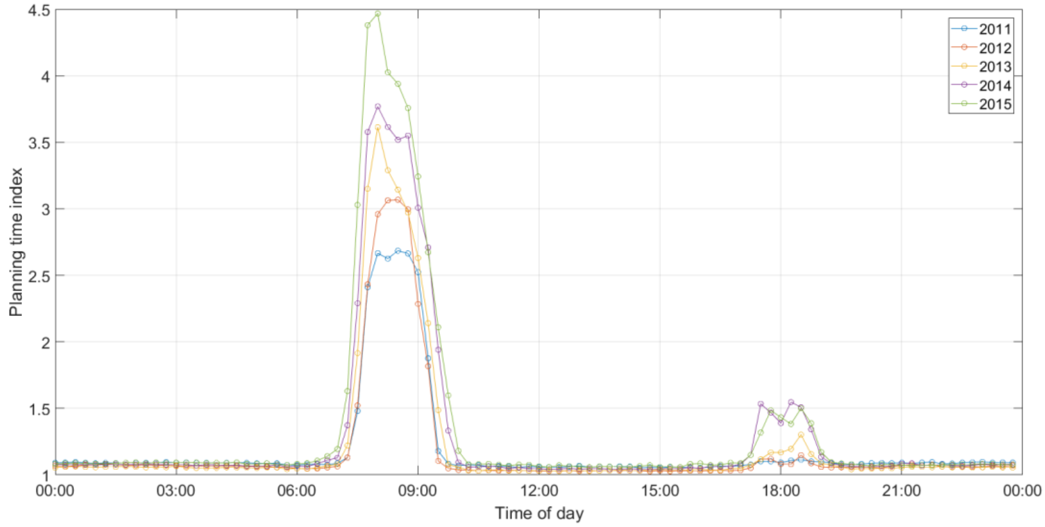

Figure 4.9: TTR Variability Pattern of Segment 125N04788 in 5 years

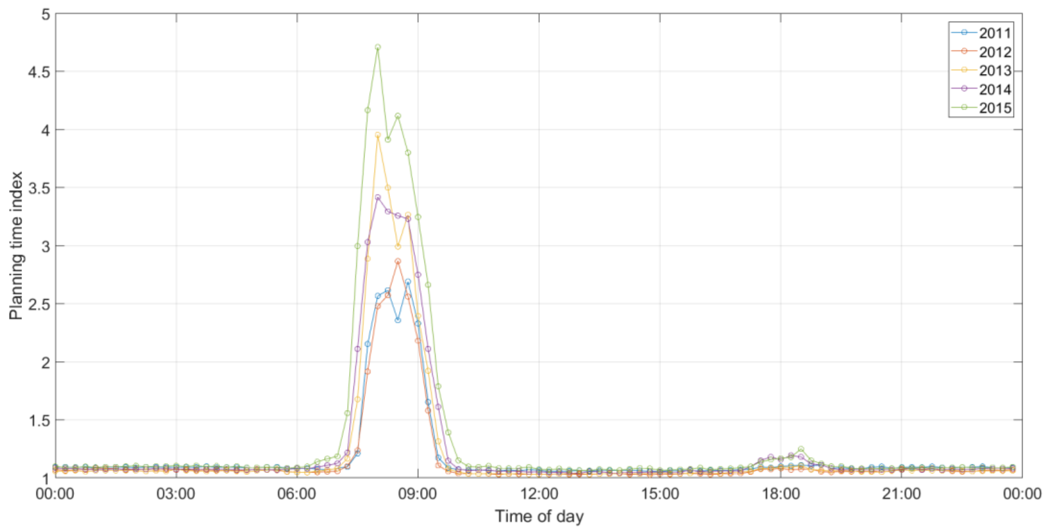

Figure 4.10: TTR Variability Pattern of Segment 125-04788 in 5 years

4.3.3 TTR Variability Pattern under Case 3

The PTIs of segment 125N04784 and 125N04785 from 2011 to 2015 are shown in Figure 4.11 and 4.12. These two sections are located adjacent to Charlotte downtown area. The volume of inbound traffic during AM hours and outbound traffic during PM hours are both high and therefore contributes to the frequent congestion under double peak condition. Similar to case 1 and 2, in the year 2015, these two segments had obvious higher PTI values during peak hours than those in the years of 2011-2014. The condition like this may also be explained by the potential reason like adverse weather and accident that contribute to the worsening of the traffic condition in the year 2015.

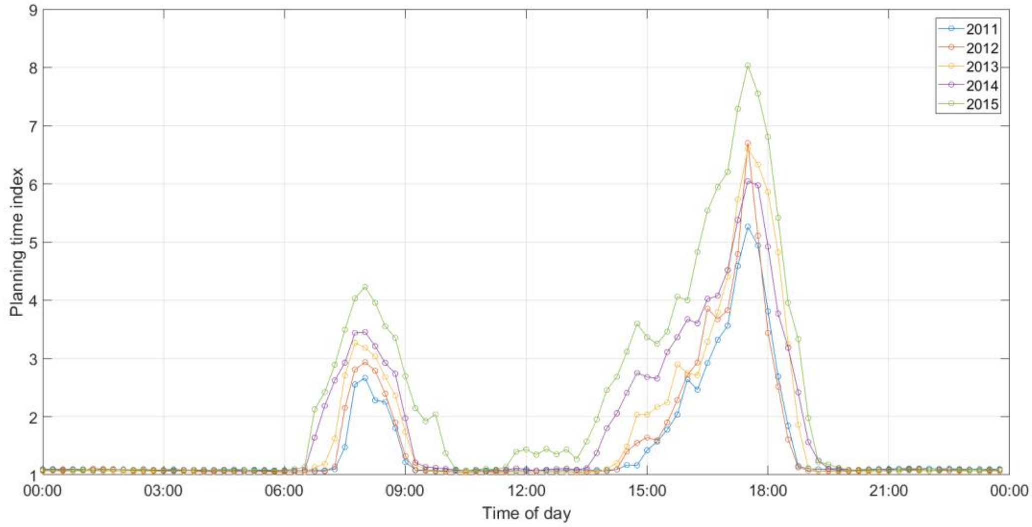

Figure 4.11: TTR Variability Pattern of Segment 125N04784 in 5 years

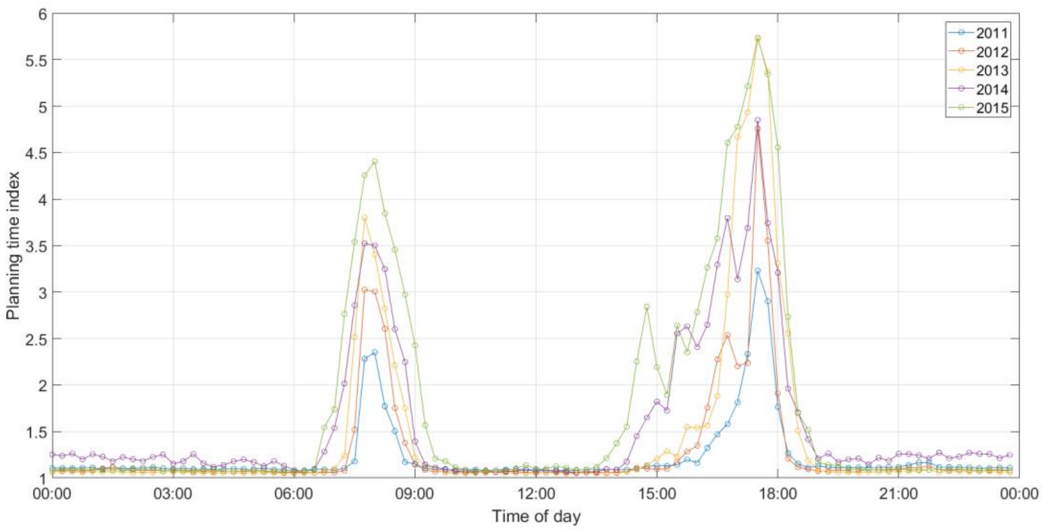

Figure 4.12: TTR Variability Pattern of Segment 125N04785 in 5 years

4.3.4 TTR Variability Pattern under Case 4

The PTIs of segment 125-04790 and 125N04791 from 2011 to 2015 are shown in Figure 4.13 and 4.14. These two sections are located far away from Charlotte downtown area. The traffic volumes during both AM and PM hours are low and therefore contributes to the no peak condition. The variation of PTIs throughout the day of each year do not change significantly (from 1.02 to 1.13 and 1.04 to 1.15, respectively).

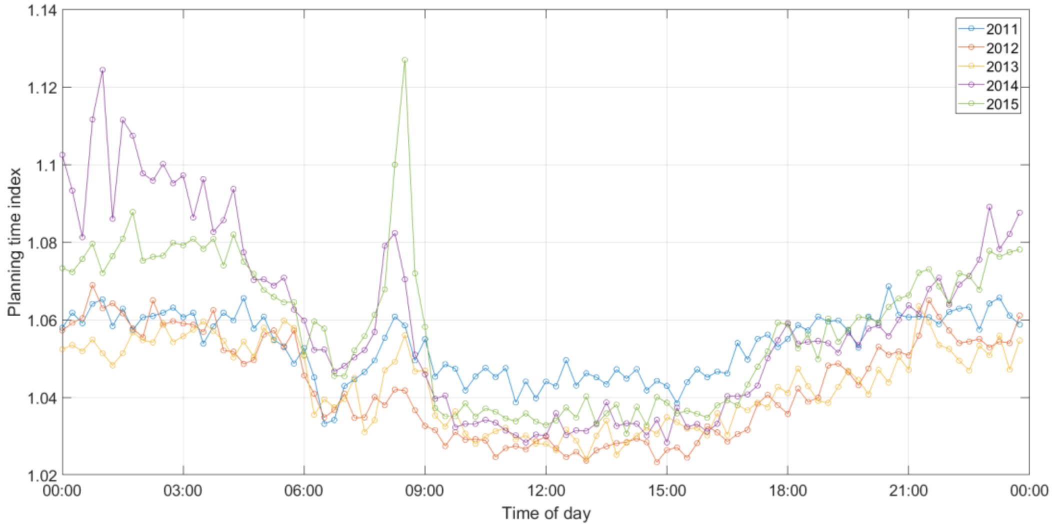

Figure 4.13: TTR Variability Pattern of Segment 125-04790 in 5 years

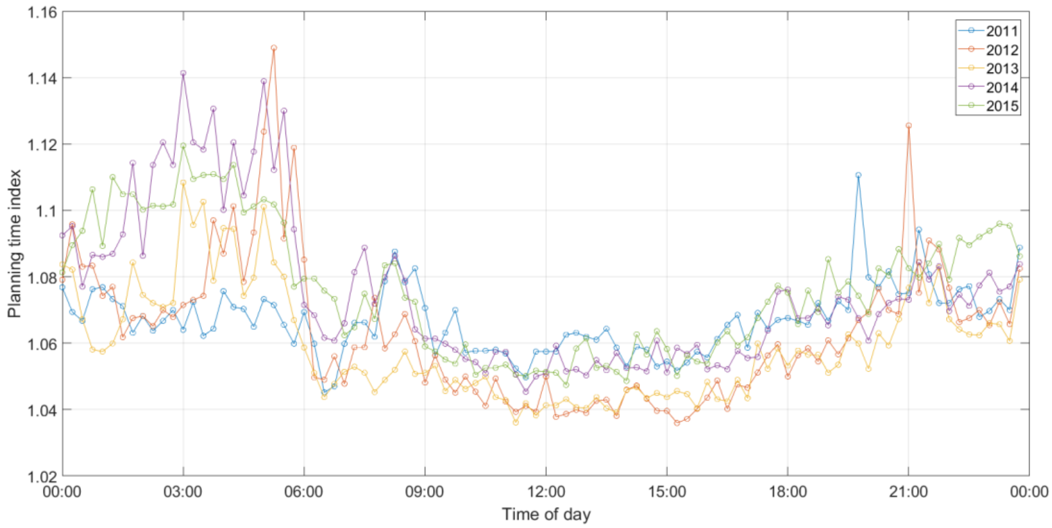

Figure 4.14: TTR Variability Pattern of Segment 125N04791 in 5 years

4.4 TTR Variability Patterns of Different DOW

4.4.1 TTR Variability Pattern of Different DOW: Case 1

The PTIs of segment 125-04779 and 125N04780 on different DOW are shown in Figure 4.15 to Figure 4.18 below. The TTR variability patterns of these two sections on weekdays are similar to the TTR variability pattern under all conditions. However, the TTR variability patterns on weekends are significantly different from weekdays. There are no PM peak characteristics of the TTR of these two segments on weekends as the PTIs throughout the day do not change significantly. The maximum PTIs on weekends of these two segments are 1.28 and 1.24, respectively. The results indicate that traffic congestion on weekends becomes less frequent and also travel demand on weekends is perhaps much lower than that on weekdays, which is consistent with previous studies (Chen et al., 2017, Chen et al., 2018)

The PTIs of segment 125-04779 and 125N04780 from Monday to Sunday are shown in Figure 4.19 to Figure 4.20 below, and the average PTIs are shown in Table 4.2. The PTI ranking result shows that: for the segments showing the PM peak characteristics, the travel time on Friday is least reliable. This result is consistent with a previous study (Wang et al., 2016).

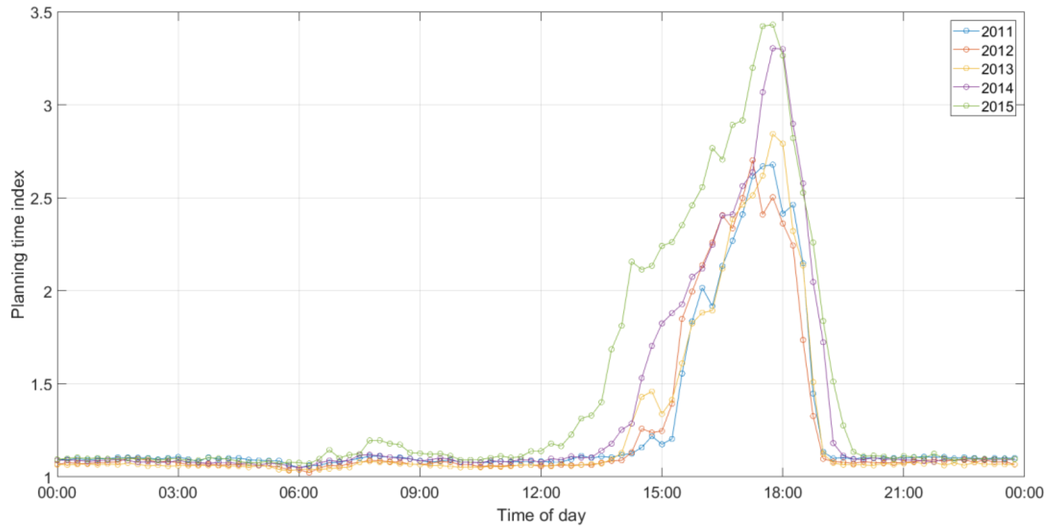

Figure 4.15: TTR Variability Pattern of Segment 125-04779 on Weekdays

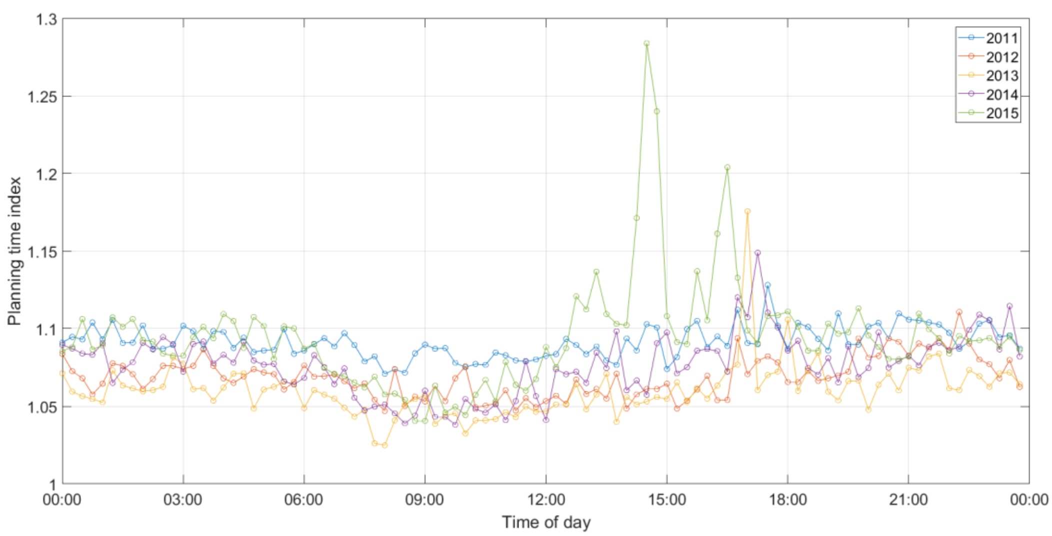

Figure 4.16: TTR Variability Pattern of Segment 125-04779 on Weekends

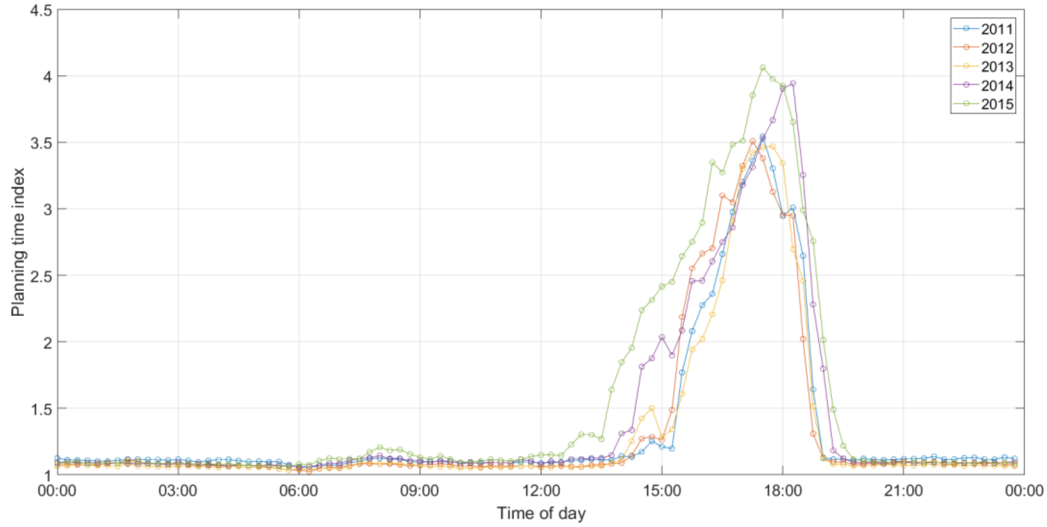

Figure 4.17: TTR Variability Pattern of Segment 125N04780 on Weekdays

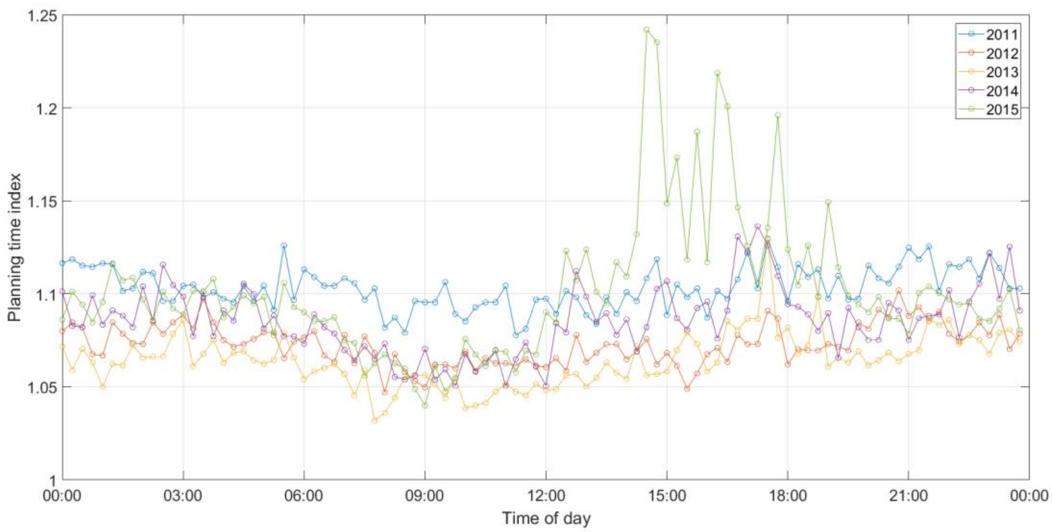

Figure 4.18: TTR Variability Pattern of Segment 125N04780 on Weekends

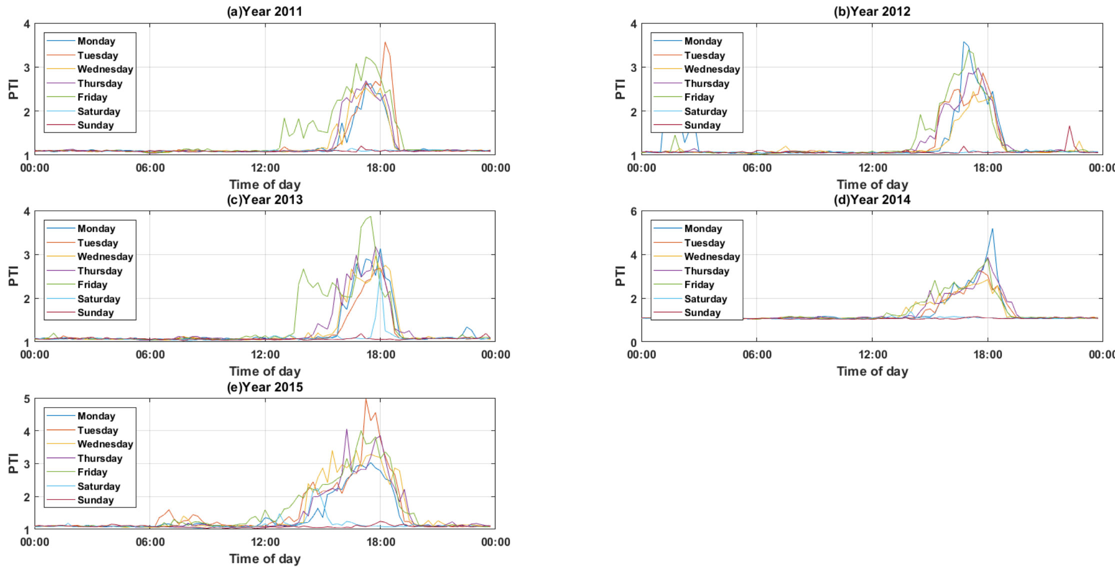

Figure 4.19: TTR Variability Pattern of Segment 125-04779 from Monday to Sunday

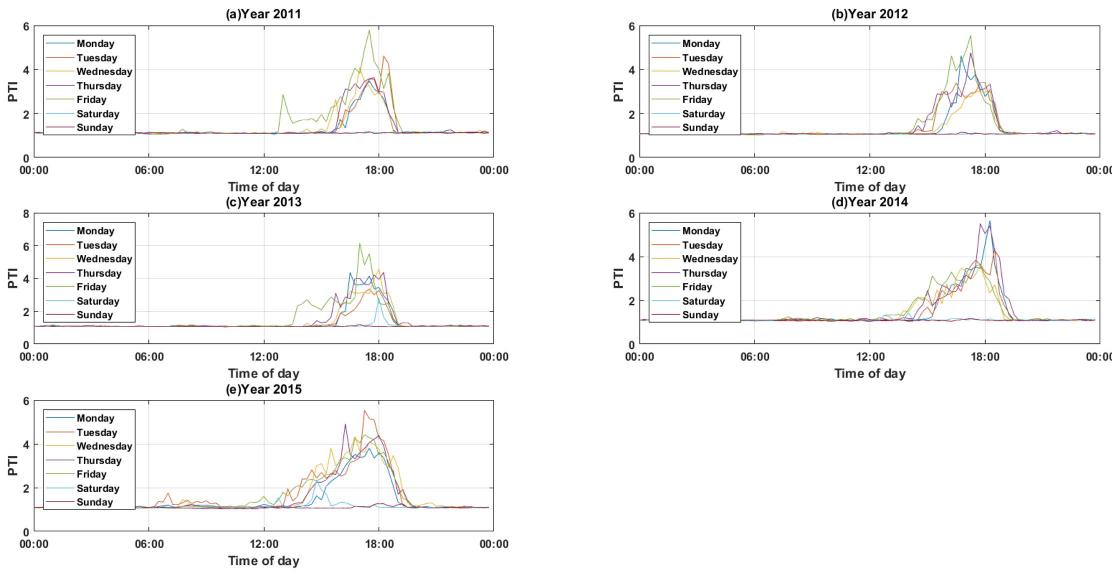

Figure 4.20: TTR Variability Pattern of Segment 125N04780 from Monday to Sunday

Table 4.2: **Average PTIs from Monday to Sunday (Case 1)**

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Segment 125-04779							
Average PTI	1.29	1.30	1.30	1.32	1.40	1.10	1.08
Rank	5	3	4	2	1	6	7
Segment 125N04780							
Average PTI	1.37	1.39	1.38	1.44	1.51	1.11	1.09
Rank	5	3	4	2	1	6	7

4.4.2 TTR Variability Pattern of Different DOW: Case 2

The PTIs of segment 125N04788 and 125-04788 on different DOW are shown in Figure 4.21 to Figure 4.24 below. Similar to case 1, the TTR variability patterns of these two sections on weekdays are similar to the TTR variability pattern under all conditions and the patterns on weekends are significantly different from weekdays. There are no AM peak characteristics of the TTR of these two segments on weekends as the PTIs throughout the day do not change significantly. The maximum PTIs on weekends of these two segments are 1.34 and 1.21, respectively. The results indicate that traffic congestion on weekends becomes less frequent and also travel demand of these two segments on weekends is perhaps much lower than that on weekdays.

The PTIs of segment 125N04788 and 125-04788 from Monday to Sunday are shown in Figure 4.25 to Figure 4.26 below, and the average PTIs are shown in Table 4.3. The PTI ranking result shows that: for the segments showing the AM peak characteristics, the travel time on Tuesday is least reliable.

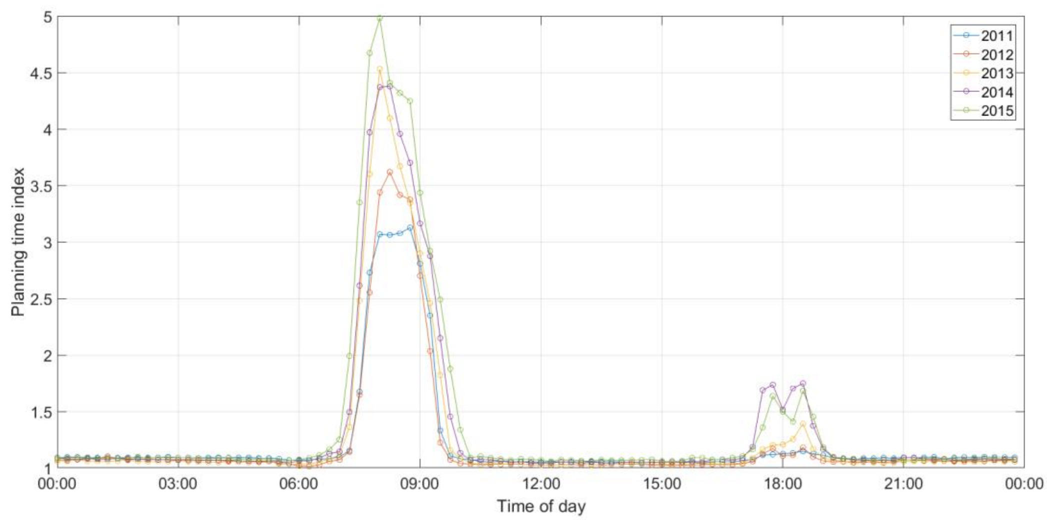

Figure 4.21: TTR Variability Pattern of Segment 125N04788 on Weekdays

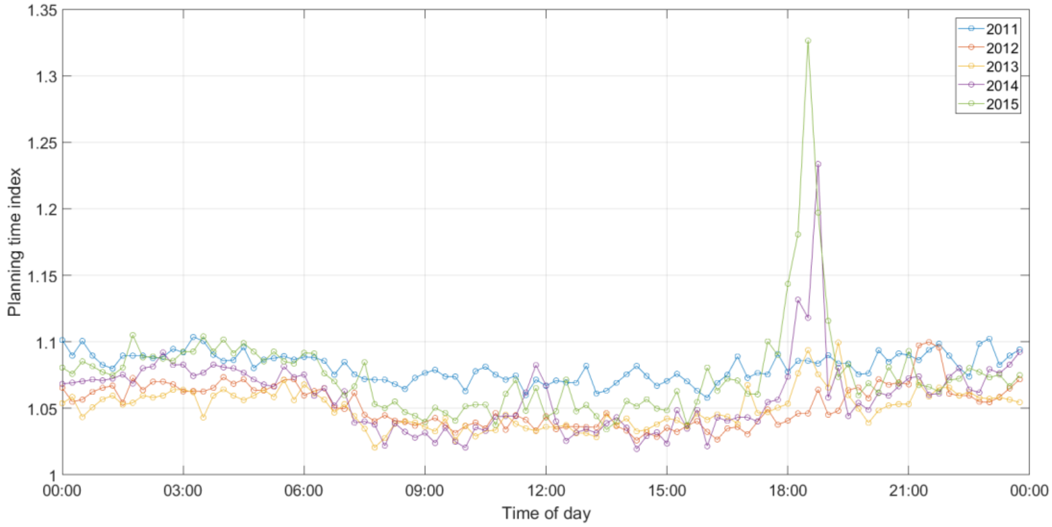

Figure 4.22: TTR Variability Pattern of Segment 125N04788 on Weekends

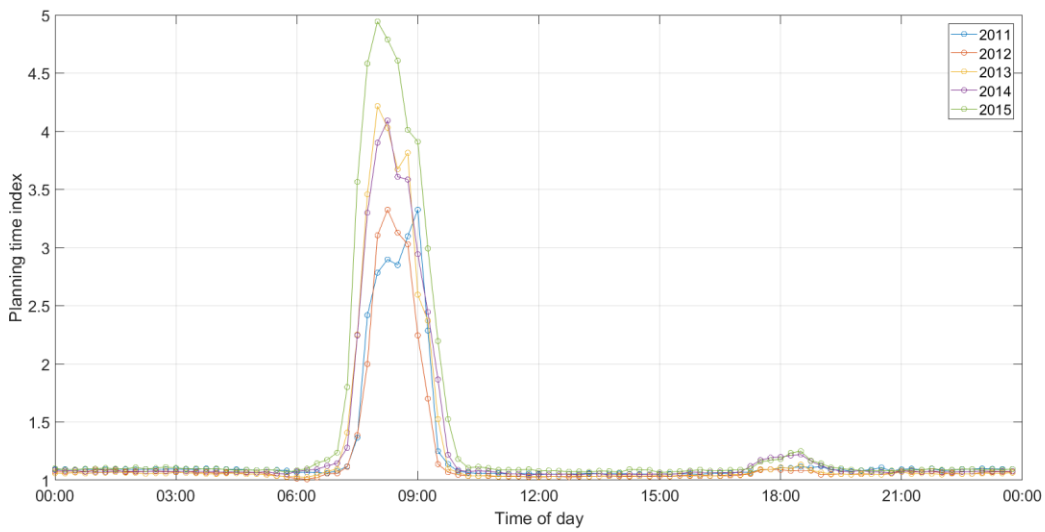

Figure 4.23: TTR Variability Pattern of Segment 125-04788 on Weekdays

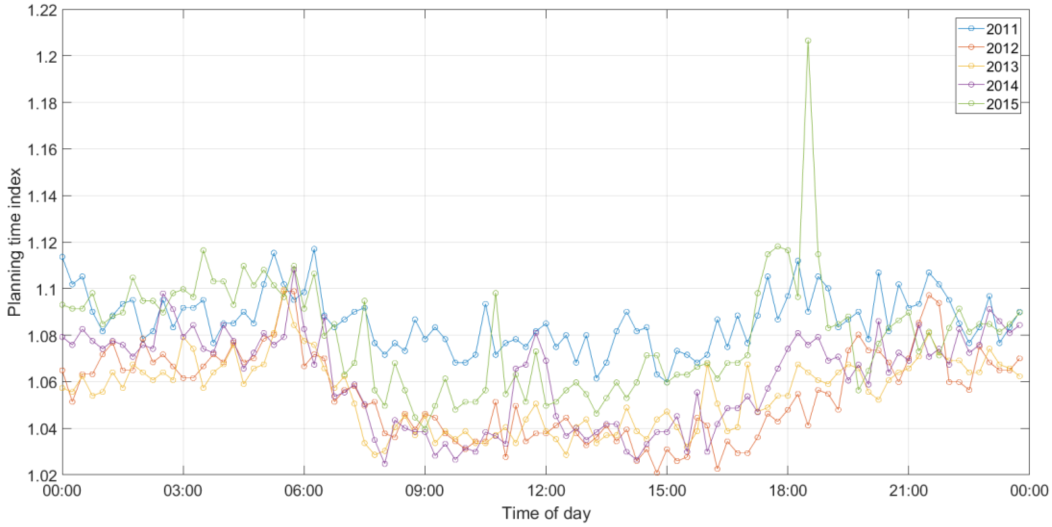

Figure 4.24: TTR Variability Pattern of Segment 125-04788 on Weekends

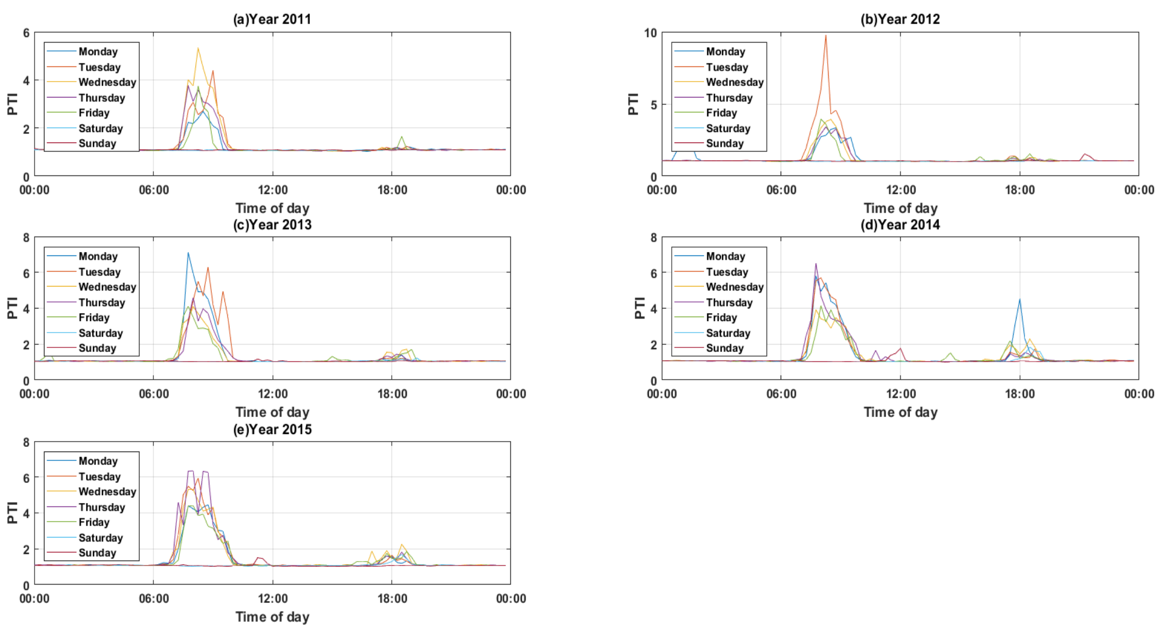

Figure 4.25: TTR Variability Pattern of Segment 125N04788 from Monday to Sunday

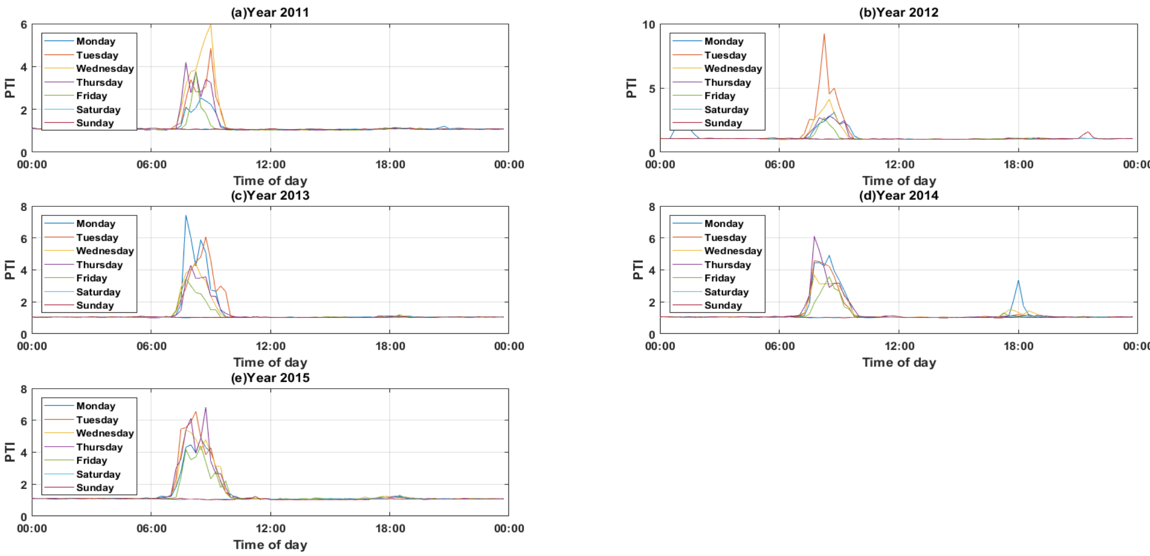

Figure 4.26: TTR Variability Pattern of Segment 125-04788 from Monday to Sunday

Table 4.3: Average PTIs from Monday to Sunday (Case 2)

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Segment 125N04788							
Average PTI	1.28	1.32	1.28	1.27	1.18	1.06	1.06
Rank	3	1	2	4	5	7	6
Segment 125-04788							
Average PTI	1.32	1.37	1.31	1.31	1.25	1.07	1.07
Rank	2	1	4	3	5	6	7

4.4.3 TTR Variability Pattern of Different DOW: Case 3

The PTIs of segment 125N04784 and 125-04785 on different DOW are shown in Figure 4.27 to Figure 4.30 below. Similar to case 1, the TTR variability patterns of these two sections on weekdays are similar to the TTR variability pattern under all conditions and the patterns on weekends are significantly different from weekdays. The PTIs of these two sections on weekends do not change significantly in most of the time. The unique PM peak pattern of segment 125N04784 on weekends in the year 2015 may be explained by the potential reason that higher accident rate of the year 2015.

The PTIs of segment 125N04784 and 125N04785 from Monday to Sunday are shown in Figure 4.31 to Figure 4.32 below, and the average PTIs are shown in Table 4.4. The PTI ranking result shows that: for the segments showing the double peak characteristics, the travel time on Friday is least reliable.

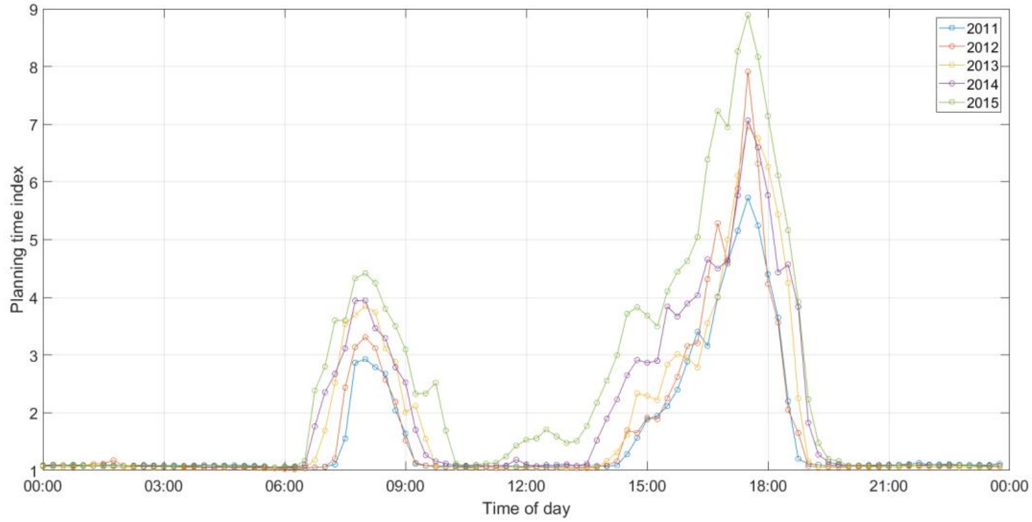

Figure 4.27: TTR Variability Pattern of Segment 125N04784 on Weekdays

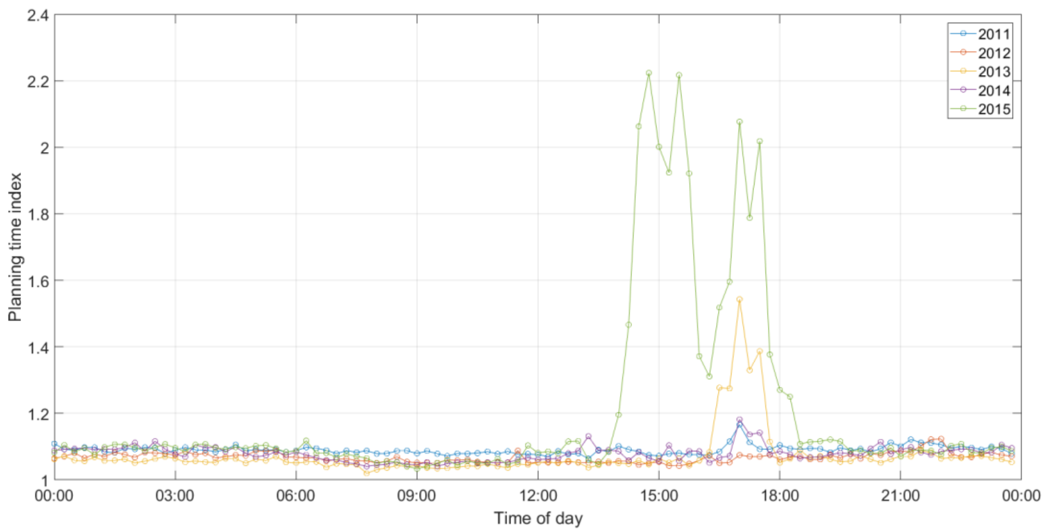

Figure 4.28: TTR Variability Pattern of Segment 125N04784 on Weekends

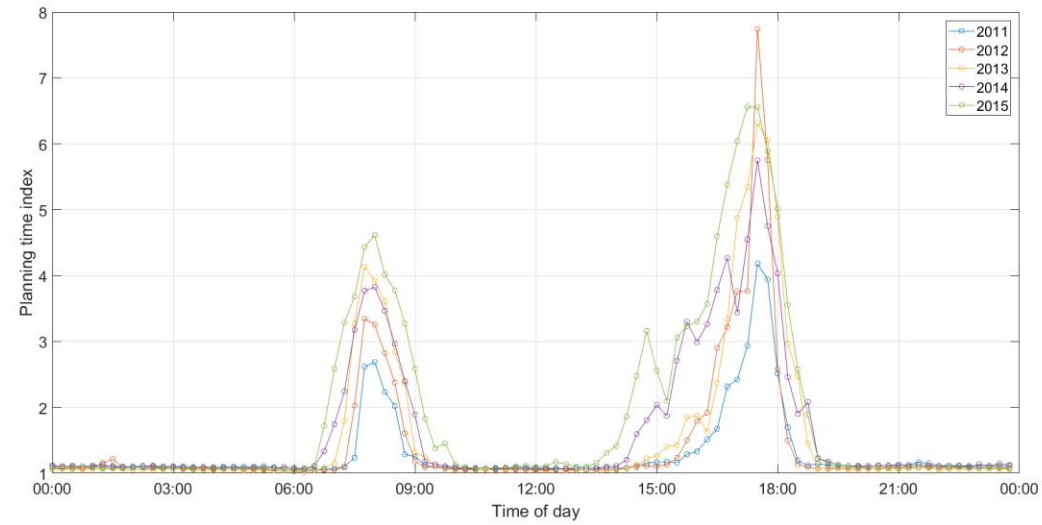

Figure 4.29: TTR Variability Pattern of Segment 125N04785 on Weekdays

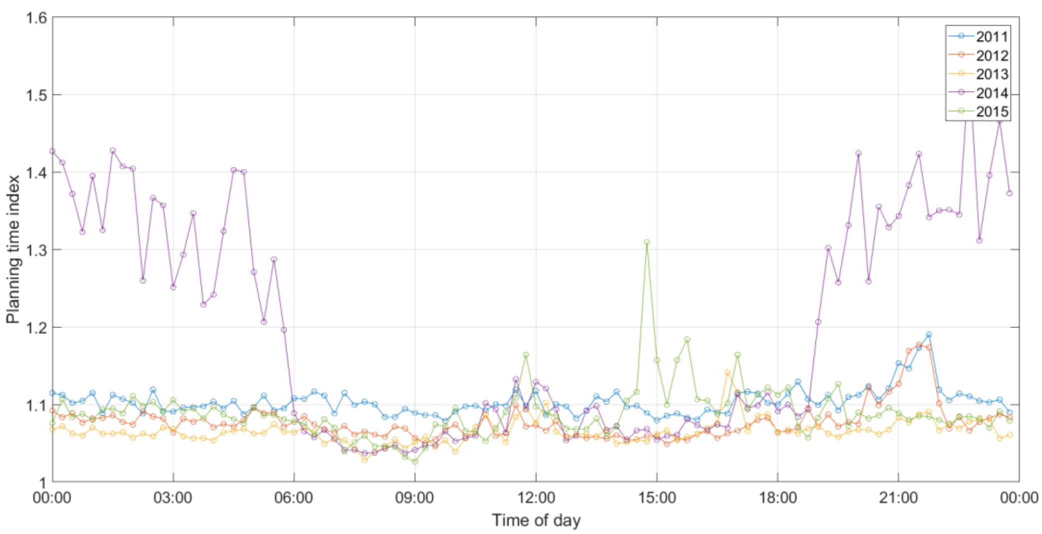

Figure 4.30: TTR Variability Pattern of Segment 125N04785 on Weekends

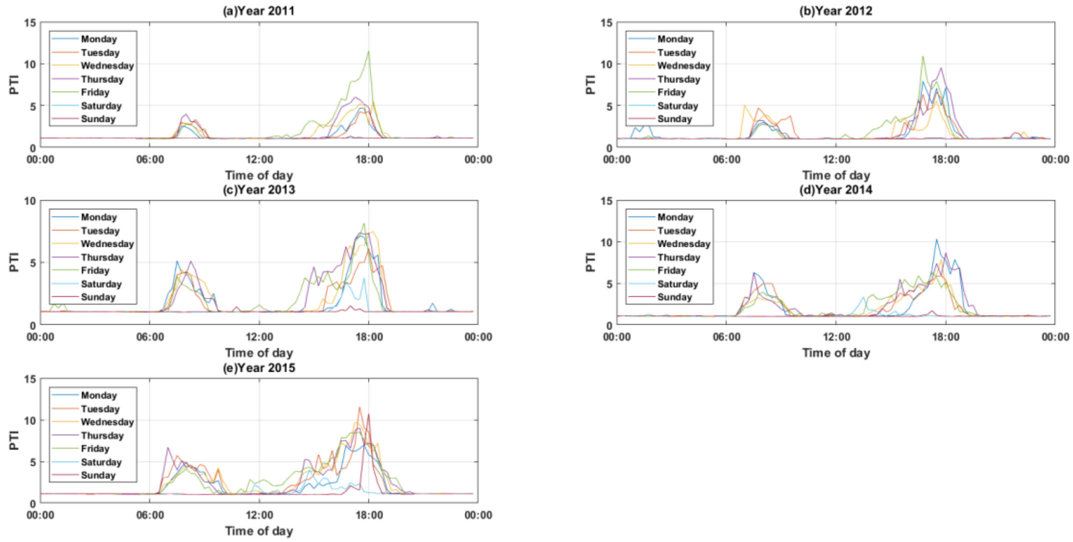

Figure 4.31: TTR Variability Pattern of Segment 125N04784 from Monday to Sunday

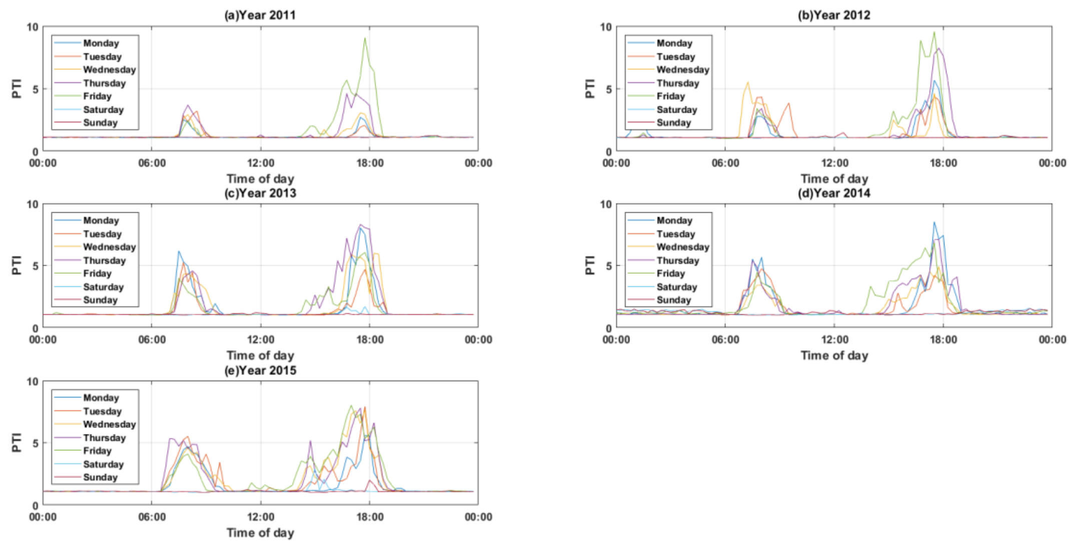

Figure 4.32: TTR Variability Pattern of Segment 125N04785 from Monday to Sunday

Table 4.4: **Average PTIs from Monday to Sunday (Case 3)**

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Segment 125N04784							
Average PTI	1.74	1.78	1.85	1.97	2.02	1.15	1.12
Rank	5	4	3	2	1	6	7
Segment 125N04785							
Average PTI	1.49	1.46	1.57	1.73	1.77	1.11	1.11
Rank	4	5	3	2	1	6	7

4.4.4 TTR Variability Pattern of Different DOW: Case 4

The PTIs of segment 125-04790 and 125N04791 on different DOW are shown in Figure 4.33 to Figure 4.36 below. The PTIs of two segments during both weekdays and weekends do not change significantly, the maximum PTIs of these two segments are all less than 1.18. The results indicate that the traffic congestions on these two segments are not frequent on both weekdays and weekends.

The PTIs of segment 125-04790 and 125N04791 from Monday to Sunday are shown in Figure 4.37 to Figure 4.38 below, and the average PTIs are shown in Table 4.5. The PTI ranking result shows that: for the segments showing no peak characteristics, average PTIs of each DOW do not change significantly (from 1.05 to 1.07 and 1.07 to 1.09, respectively).

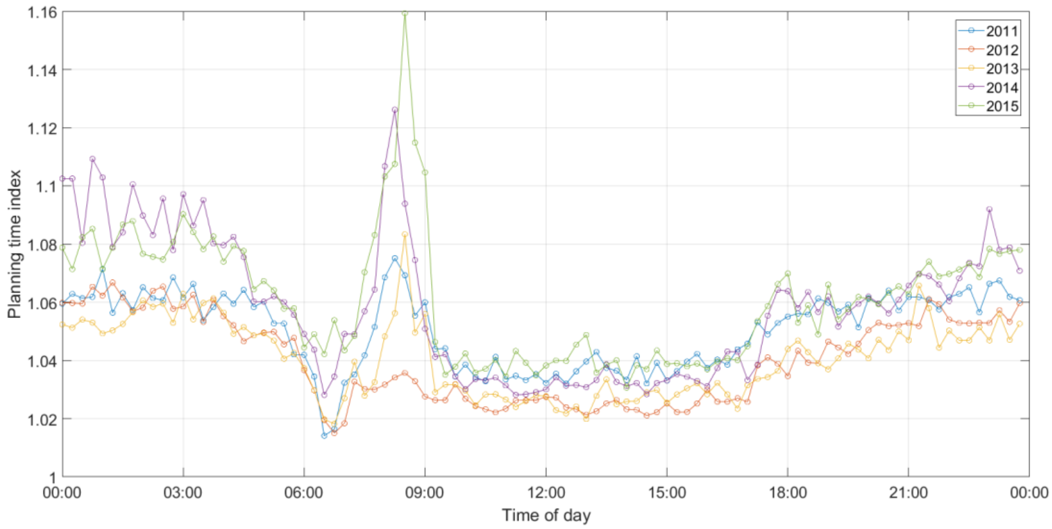

Figure 4.33: TTR Variability Pattern of Segment 125-04790 on Weekdays

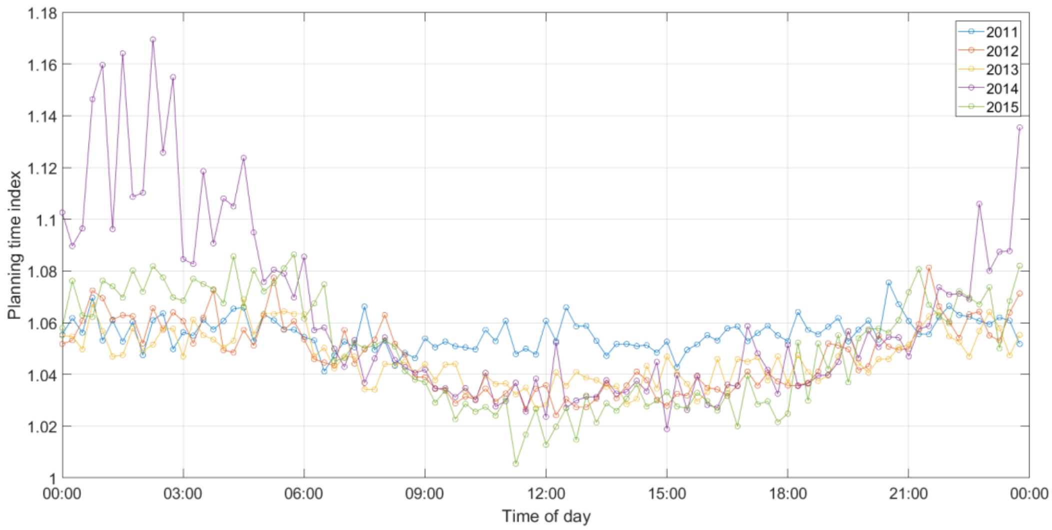

Figure 4.34: TTR Variability Pattern of Segment 125-04790 on Weekends

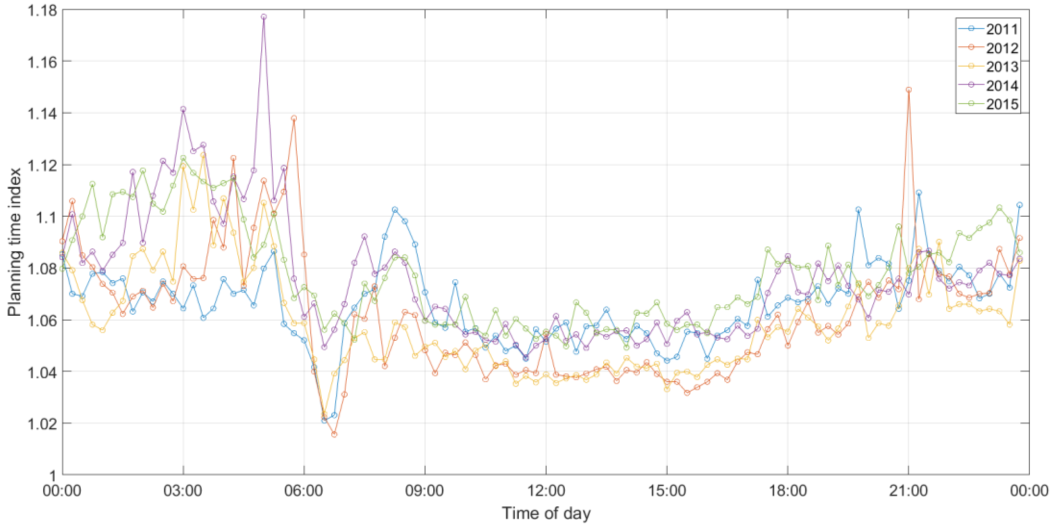

Figure 4.35: TTR Variability Pattern of Segment 125N04791 on Weekdays

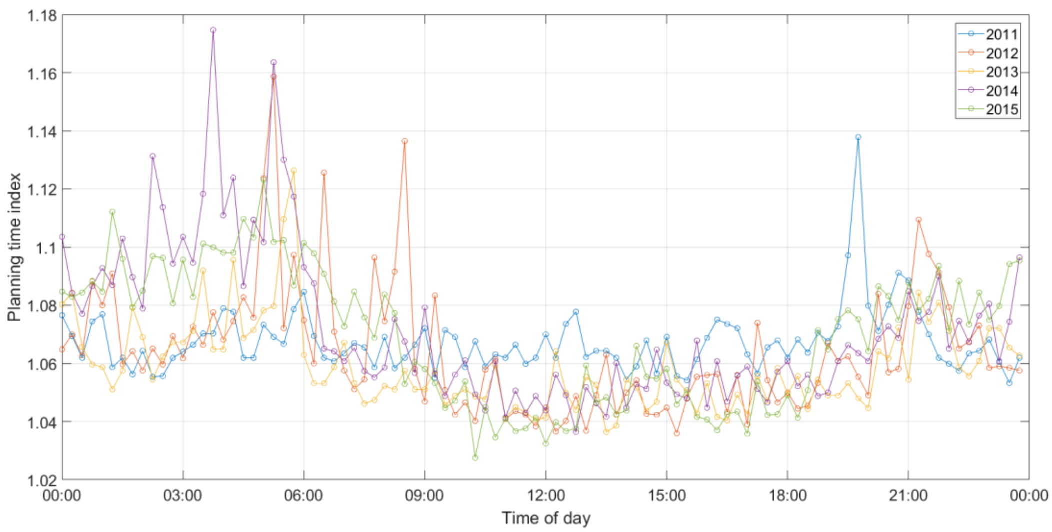

Figure 4.36: TTR Variability Pattern of Segment 125N04791 on Weekends

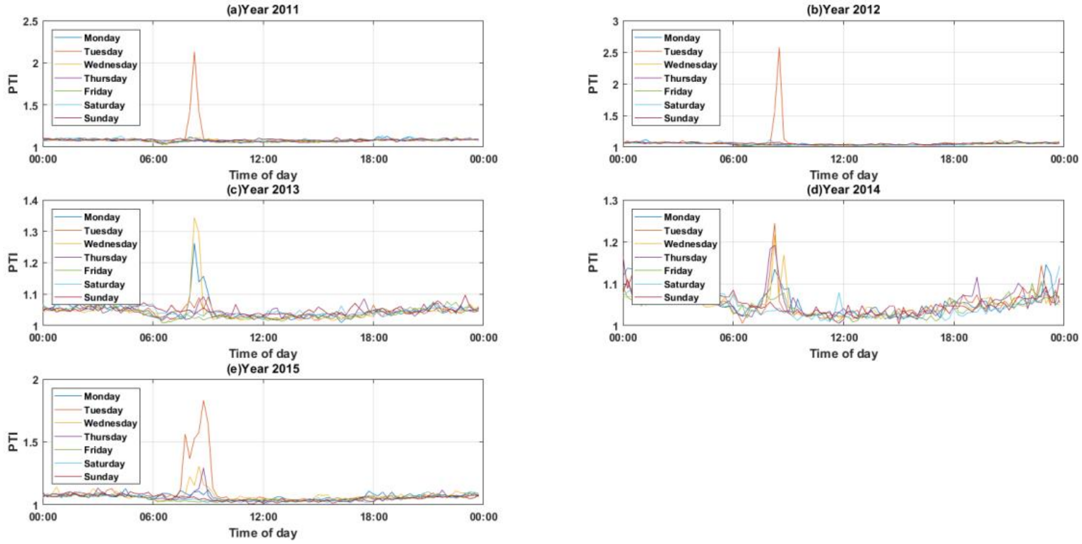

Figure 4.37: TTR Variability Pattern of Segment 125-04790 from Monday to Sunday

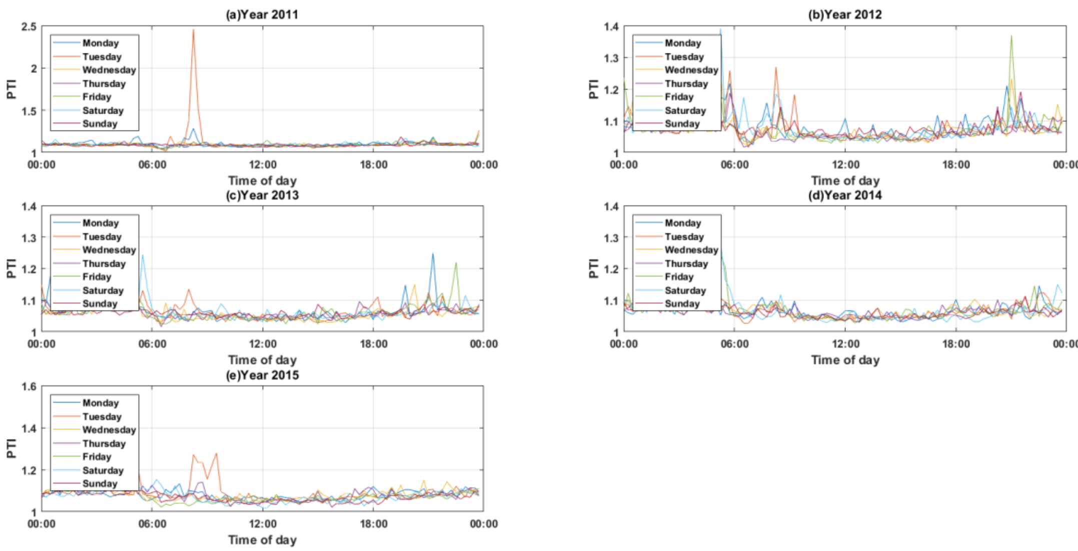

Figure 4.38: TTR Variability Pattern of Segment 125N04791 from Monday to Sunday

Table 4.5: Average PTIs from Monday to Sunday (Case 4)

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Segment 125-04790							
Average PTI	1.06	1.07	1.06	1.06	1.05	1.06	1.06
Rank	3	1	4	6	7	5	2
Segment 125N04791							
Average PTI	1.08	1.09	1.07	1.08	1.08	1.08	1.07
Rank	2	1	6	5	4	3	7

4.5 TTR Variability Pattern under Different Weather Conditions

4.5.1 TTR Variability Pattern under Different Weather Conditions: Case 1

The PTIs of segment 125-04779 and 125N04780 under different weather conditions are shown in Figure 4.39 and Figure 4.40 below. The TTR variability patterns of these two sections under normal and rain conditions are similar and the pattern is unique under the snow/ice/fog condition. In more detail, the PTIs under rain condition have obvious higher values than normal condition throughout the day. This probably suggests that rain can cause several travel problems such as visibility issues while driving a vehicle. Heavy rainfall may lead to hydroplaning, slippery surfaces for tires and road flooding. Therefore, the values of PTIs under rain condition also increase and the traffic congestion becomes more frequent. This result is consistent with other studies (Tsapakis et al. 2013, Li et al. 2016). The PTIs under snow/ice/fog condition is also higher than those under normal condition throughout the day because of the influence of road surfaces and visibility problems (Weng et al., 2013). The potential reason for the unique TTR variability pattern under the snow/fog/ice condition could be: snow/fog/ice can contribute to unexcepted condition on the roadway anytime throughout the day. This result is also consistent with a previous study (Yazici et al., 2011).

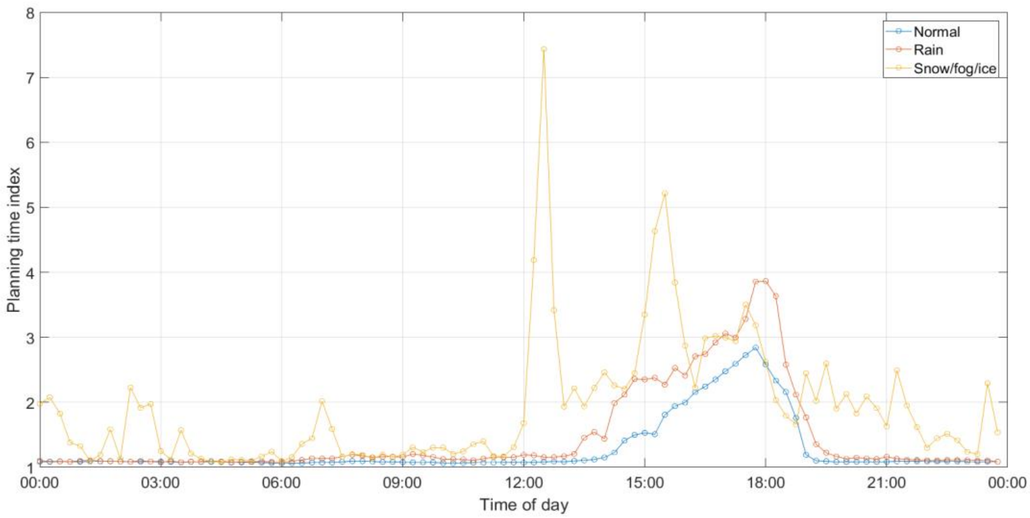

Figure 4.39: TTR Variability Pattern of Segment 125-04779 under Different Weather Conditions

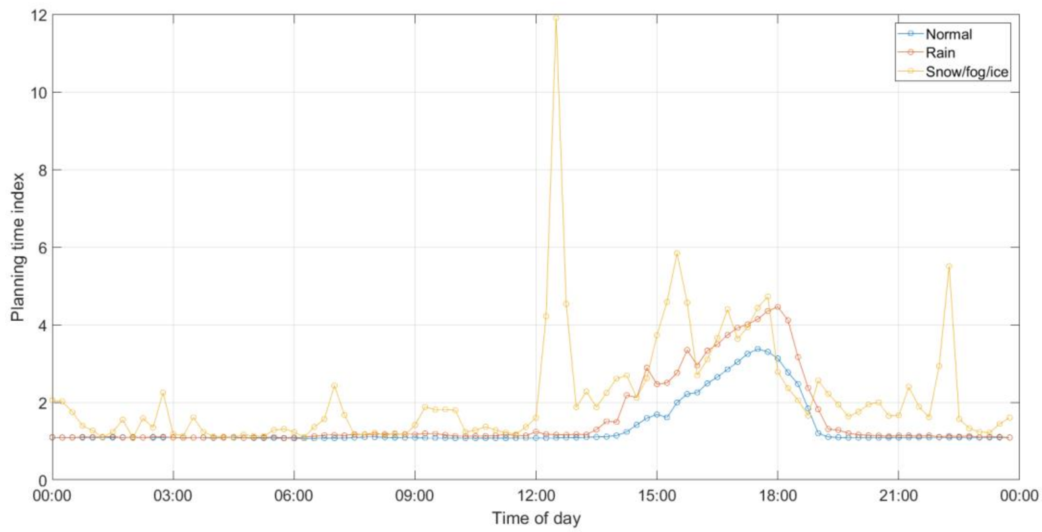

Figure 4.40: TTR Variability Pattern of Segment 125N04780 under Different Weather Conditions

4.5.2 TTR Variability Pattern under Different Weather Conditions: Case 2

The PTIs of segment 125N04788 and 125-04788 under different weather conditions are shown in Figure 4.41 and Figure 4.42 below. Similar to case 1, the PTIs under rain condition have obvious higher values than those under normal condition throughout the day. And the PTIs under the snow/ice/fog condition are also higher than the PTIs under normal condition throughout the day and demonstrates unique variability pattern.

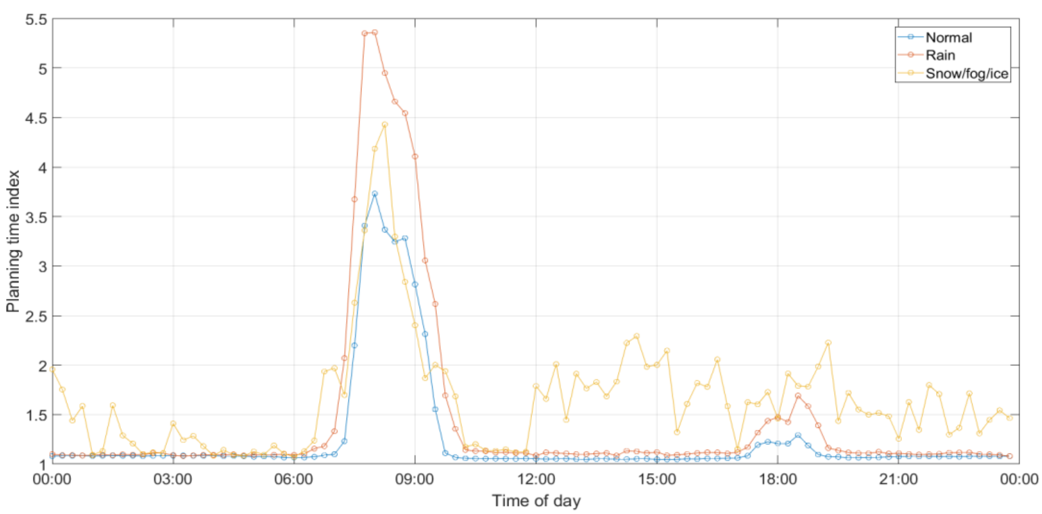

Figure 4.41: TTR Variability Pattern of Segment 125N04788 under Different Weather Conditions

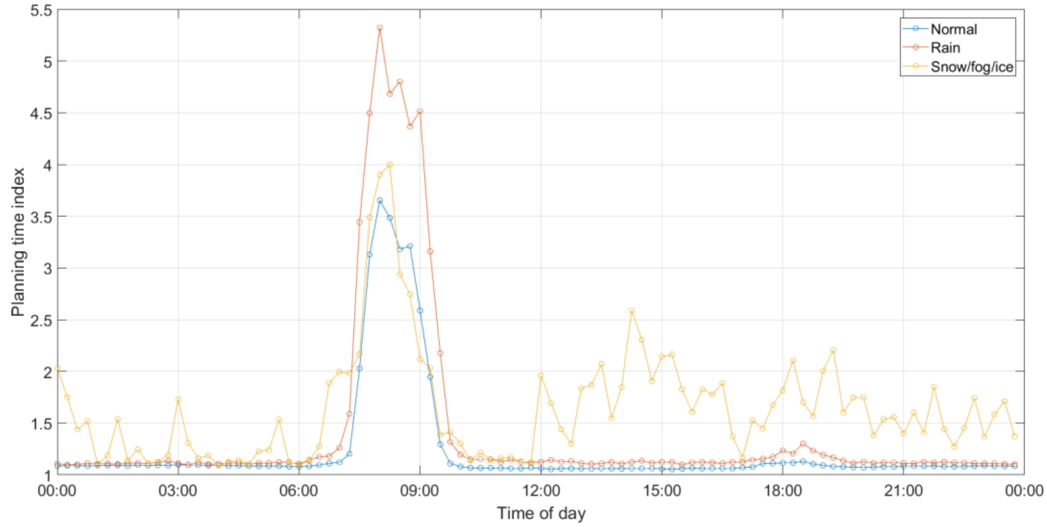

Figure 4.42: TTR Variability Pattern of Segment 125-04788 under Different Weather Conditions

4.5.3 TTR Variability Pattern under Different Weather Conditions: Case 3

The PTIs of segment 125N04784 and 125N04785 under different weather conditions are shown in Figure 4.43 and Figure 4.44 below. Similar to case 1 and 2, the PTIs under rain condition have obvious higher values than those under normal condition throughout the day. And the PTIs under the snow/ice/fog condition is also higher than the PTIs under normal condition throughout the day and demonstrates unique variability pattern.

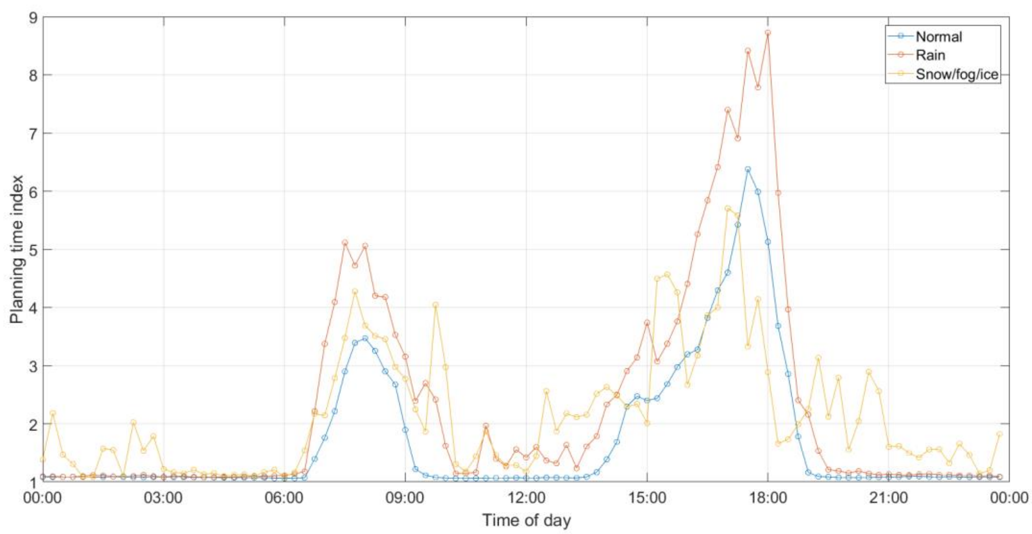

Figure 4.43: TTR Variability Pattern of Segment 125N04784 under Different Weather Conditions

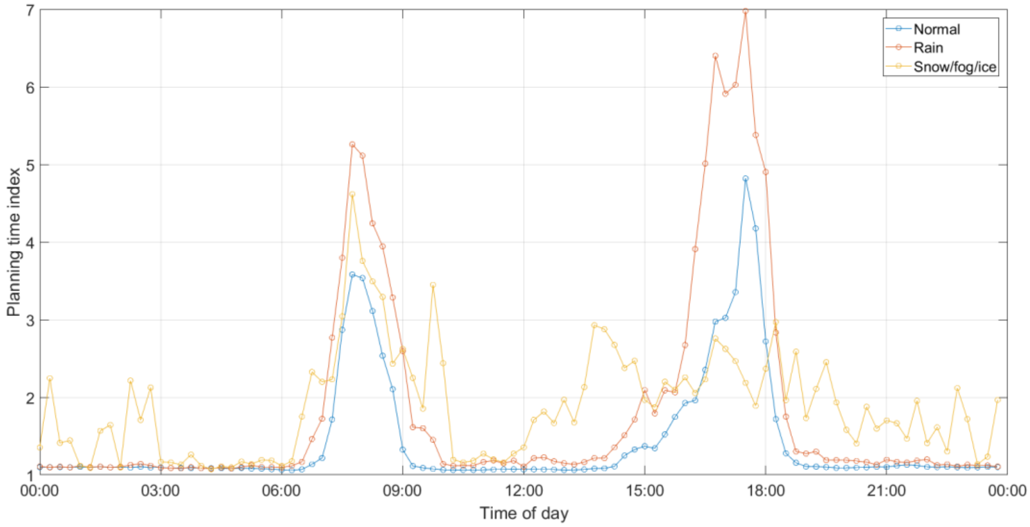

Figure 4.44: TTR Variability Pattern of Segment 125N04784 under Different Weather Conditions

4.5.4 TTR Variability Pattern under Different Weather Conditions: Case 4

The PTIs of segment 125-04790 and 125N04791 under different weather conditions are shown in Figure 4.45 and Figure 4.46 below. In more detail, the PTIs under rain condition have higher values than normal condition but not increase significantly. However, the PTIs under the snow/ice/fog condition is much higher than the PTIs under normal condition throughout the day. This result shows the adverse weather like snow, fog and ice can affect the traffic condition of the segment significantly, and the traffic congestion becomes more frequent no matter when.

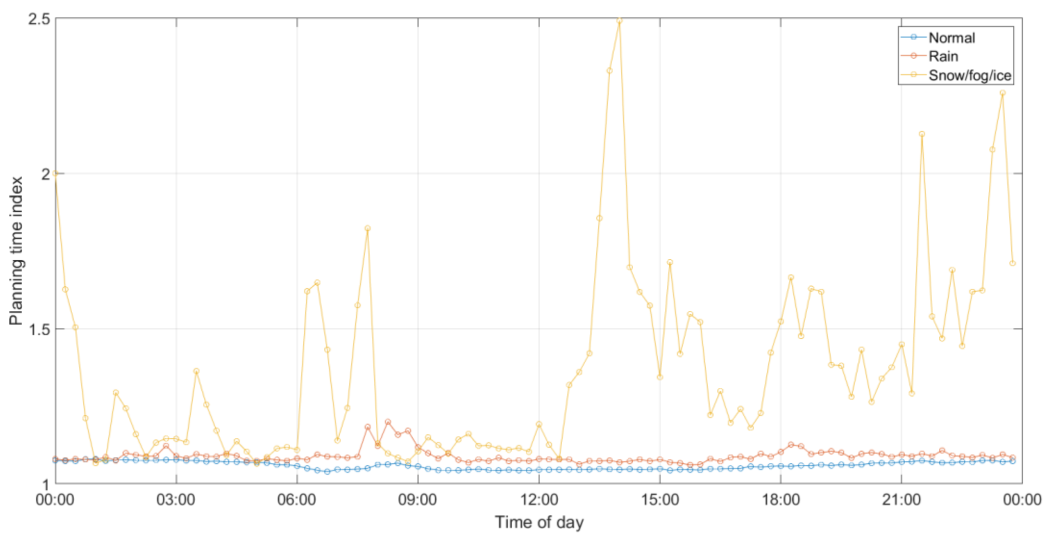

Figure 4.45: TTR Variability Pattern of Segment 125-04790 under Different Weather Conditions

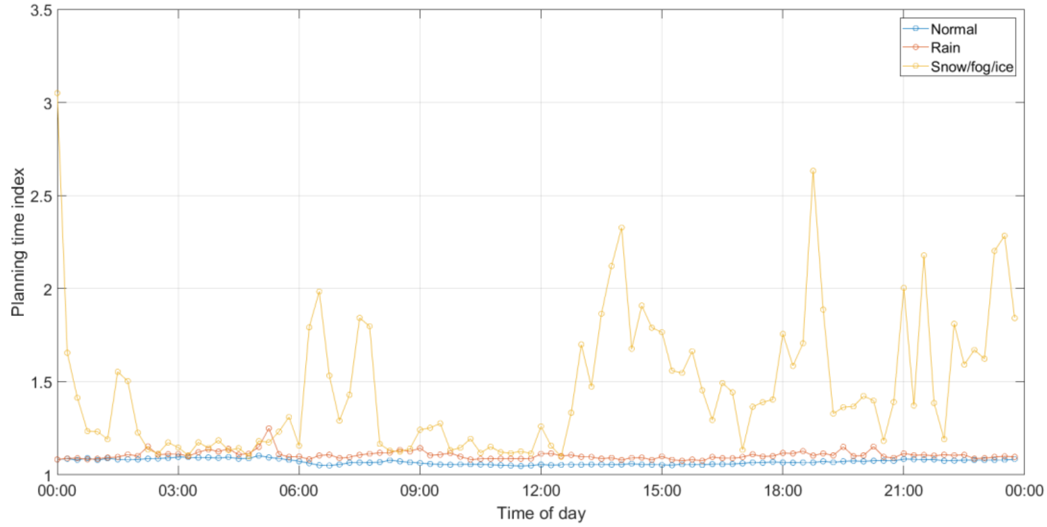

Figure 4.46: TTR Variability Pattern of Segment 125N04791 under Different Weather Conditions

4.6 Summary

This chapter describes the analysis results of TTR variability patterns. The analysis results can give a clear picture of the TTR characteristics on different DOW and under different weather conditions.

Chapter 5. TTR Prediction

5.1 Introduction

The chapter introduces the TTR prediction methodology developed and utilized in this study. The following sections are organized as follows. Section 5.2 presents the TTR prediction model. Section 5.3 shows the analysis of the TTR prediction results. Finally, section 5.4 concludes this chapter with a summary.

5.2 TTR Prediction Model

5.2.1 Linear Regression Model

Previous studies displayed numerous forecasting techniques of travel-time prediction such as regression methods and time series estimation methods. However, very few of them focus on the prediction of TTR, which is a long-term index of a segment. This section introduces a linear regression based TTR prediction method using the historical TTR data collected in five years (2011 to 2015) to predict the TTR in the year 2016, then compare the prediction result with the historical average value in five years and the 2016 ground truth data.

In order to predict the TTR in the year 2016, the input data is the historical PTI values of the selected segment in five years. The linear regression model is utilized in this study to predict the PTI in the year 2016. The linear regression equation is:

$$y_i = \beta_{0i} + \beta_{1i} X$$

Where

y_i = PTI value of segment *i*,

β_{0i}= Constant of the model of segment *i*,

β_{1i}= Estimated coefficient of the model of segment *i*,

X = Year

With the application of linear regression prediction model, the TTR values on each segment in the year 2016 are predicted both under all conditions and with the consideration of DOW.

5.2.2 Time Series Model

Exponential smoothing (ETS) model is a commonly used method in time series analysis and has been widely adopted in traffic forecasting for decades. The ETS model is an intuitive forecasting method that weights the observed time series unequally (Li et al., 2008). Recent observations are weighted more heavily than remote observations. The ETS equation (Gardner and McKenzie, 1985) is shown as follows:

$$S_t = \alpha \cdot x_t + (1 - \alpha) \cdot S_{t-1}$$

where

S_t = The output of the exponential smoothing algorithm,

α = Smoothing factor, and $0 < \alpha < 1$,

X_t= The raw data sequence

Based on the historical travel time data, the PTIs from Monday to Sunday in each year and the PTIs of each month can be calculated. Those values can be used as the input to the exponential smoothing model. The ETS model is utilized in this study to predict the PTIs from Monday to Sunday and the PTIs in each month in the year 2015.

5.3 TTR Prediction Results

5.3.1 TTR Prediction Results under All Conditions

Figures 5.1 and 5.2 below show the comparison of the prediction results, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125-04779 and segment 125N04780, respectively. The result in Table 5.1 shows: For the two segments with PM peak characteristics, the prediction model can provide a reliable prediction with the average percentage errors being 5.65% and 7.50%, respectively.

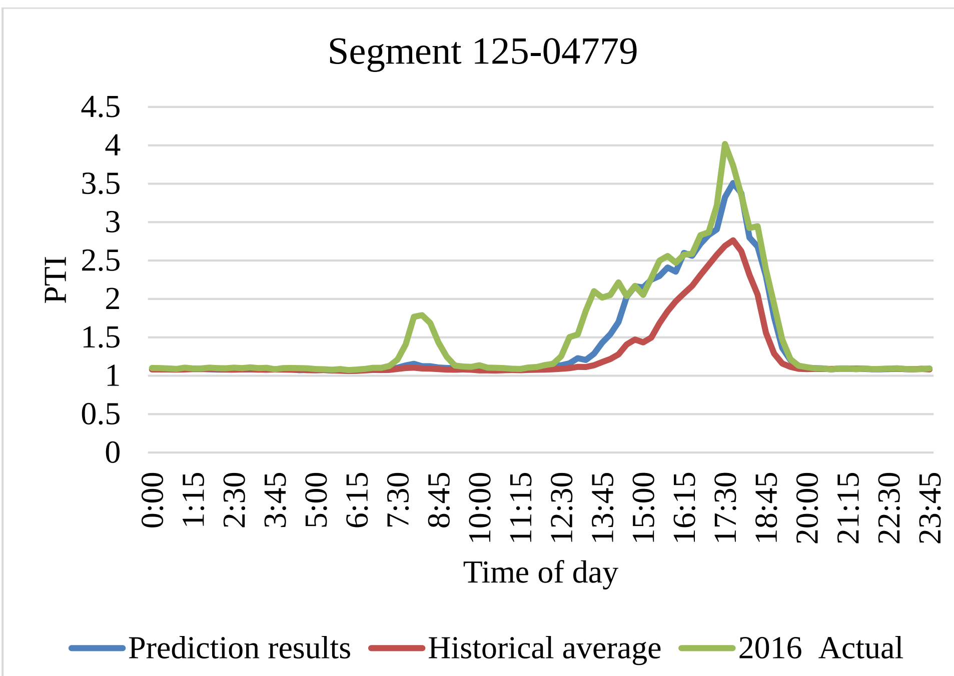

Figure 5.1: Prediction Result of Segment 125-04779

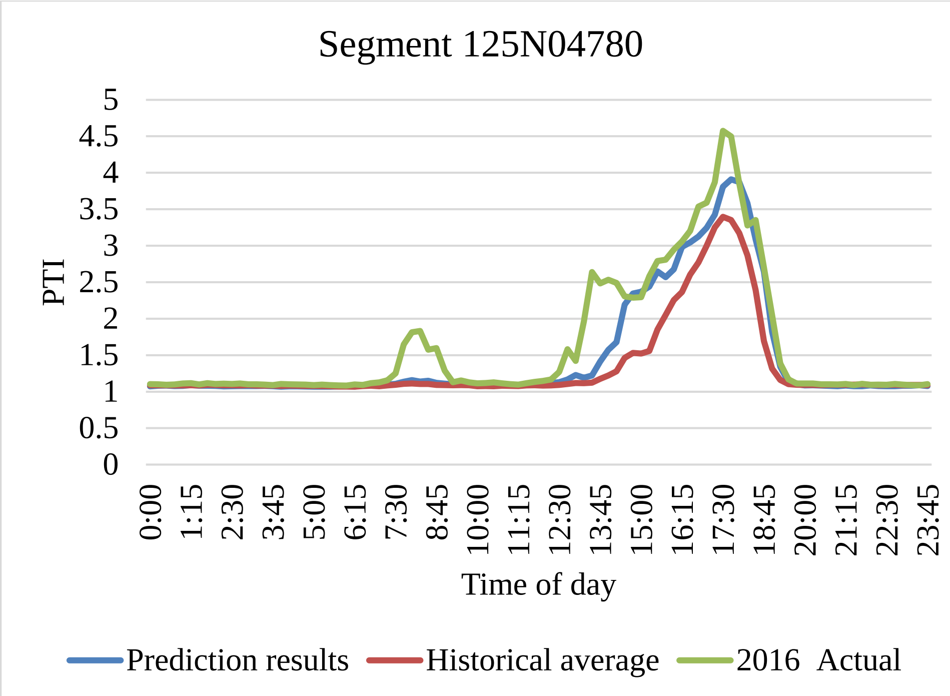

Figure 5.2: Prediction Result of Segment 125N04780

Figure 5.3 and 5.4 below show the comparison of the prediction result, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125N04788 and segment 125-04788, respectively. The result in Table 5.1 shows: For the two segments with AM peak characteristics, the prediction model can provide a reliable prediction with the average percentage error being 7.48% and 5.46%, respectively.

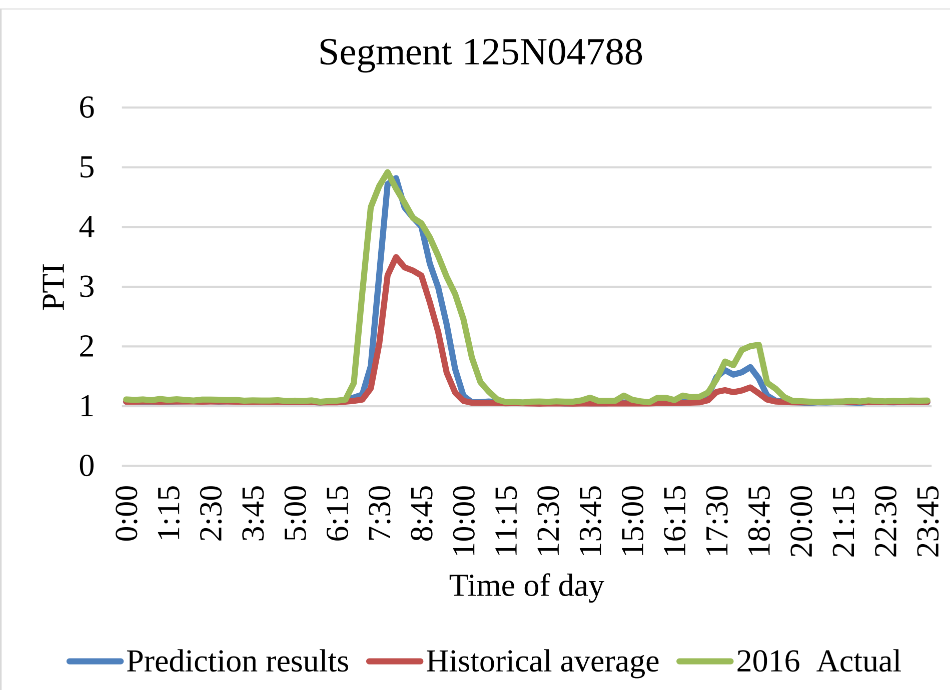

Figure 5.3: Prediction Result of Segment 125N04788

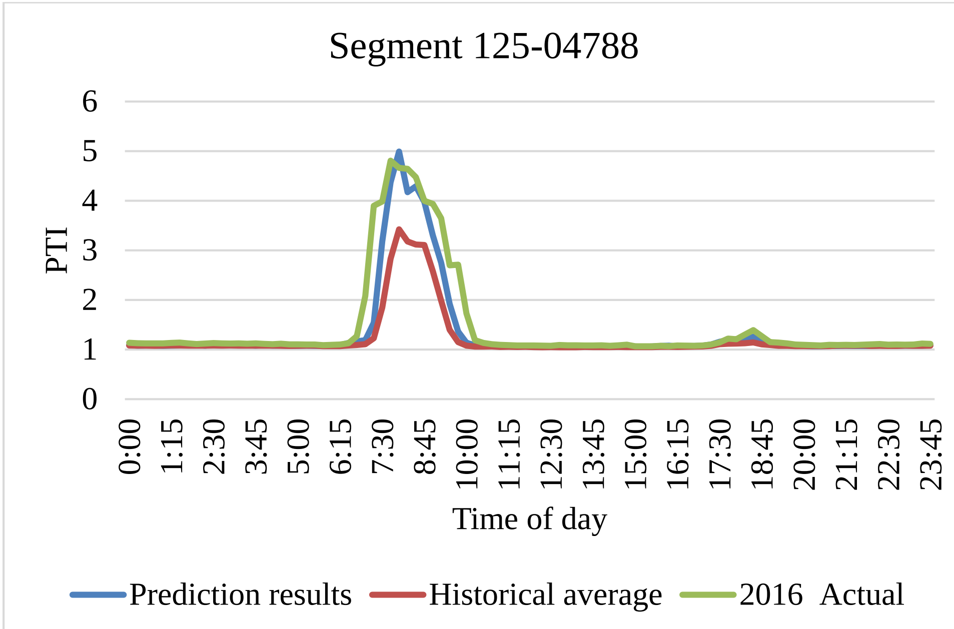

Figure 5.4: Prediction Result of Segment 125-04788

Figure 5.5 and 5.6 below show the comparison of the prediction result, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125N04784 and segment 125N04785, respectively. The result in Table 5.1 shows: For the segments with double peak characteristics, the prediction model can provide reliable prediction on segment 125N04784 with the average percentage error being 8.27%. For the segment 125N04785, the average percentage error is 18.19%, which may be explained by the unique TTR characteristic of that segment during PM peak period in the year 2016.

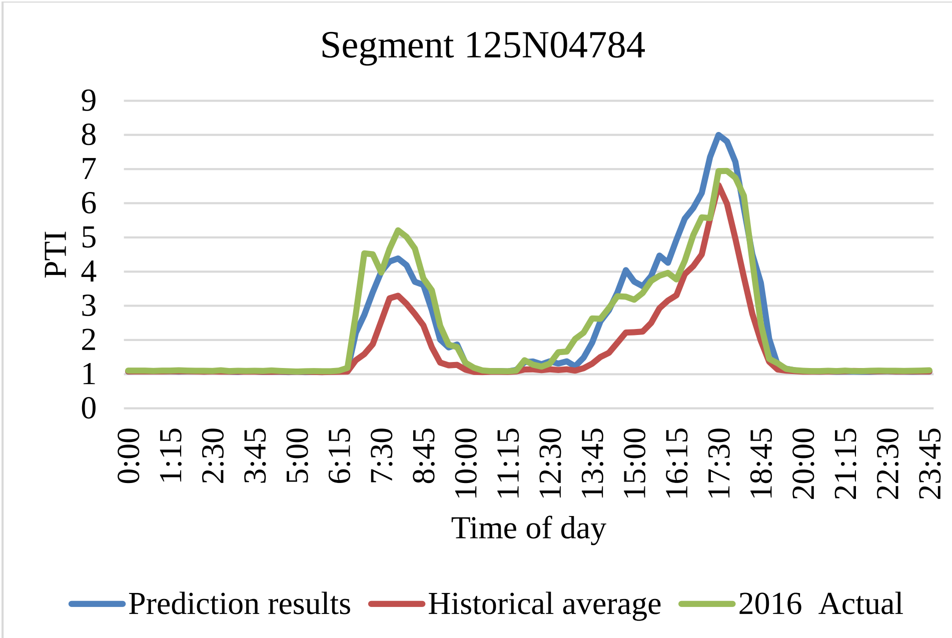

Figure 5.5: Prediction Result of Segment 125N04784

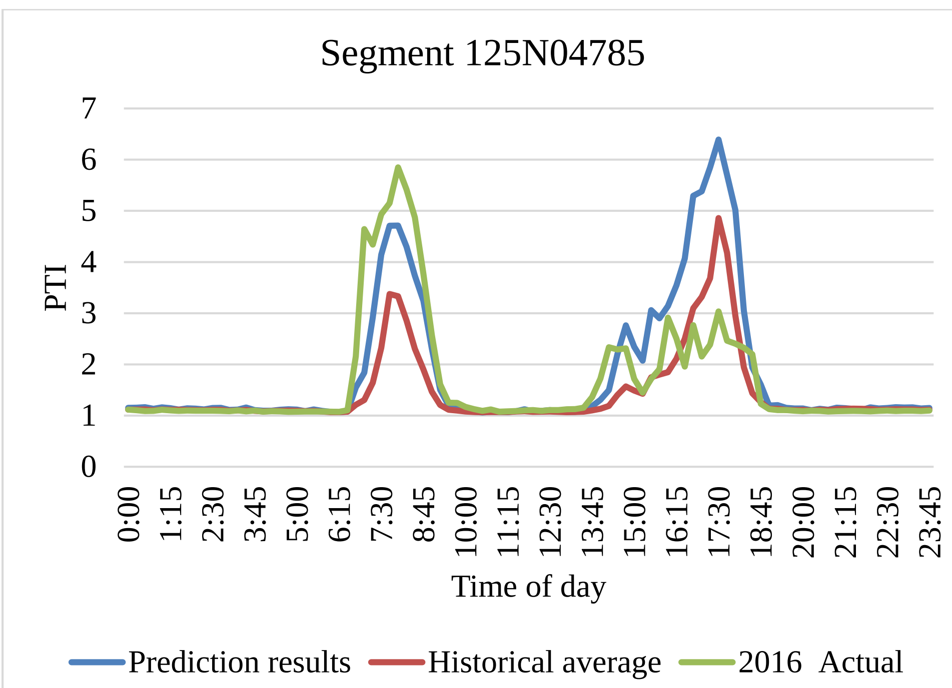

Figure 5.6: Prediction Result of Segment 125N04785

Figure 5.7 and 5.8 below show the comparison of the prediction results, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125-04790 and segment 125N04791, respectively. The result in Table 5.1 shows: For the segments with no peak characteristics, the prediction model can provide a reliable prediction with the average percentage error being 1.15% and 0.90%, respectively.

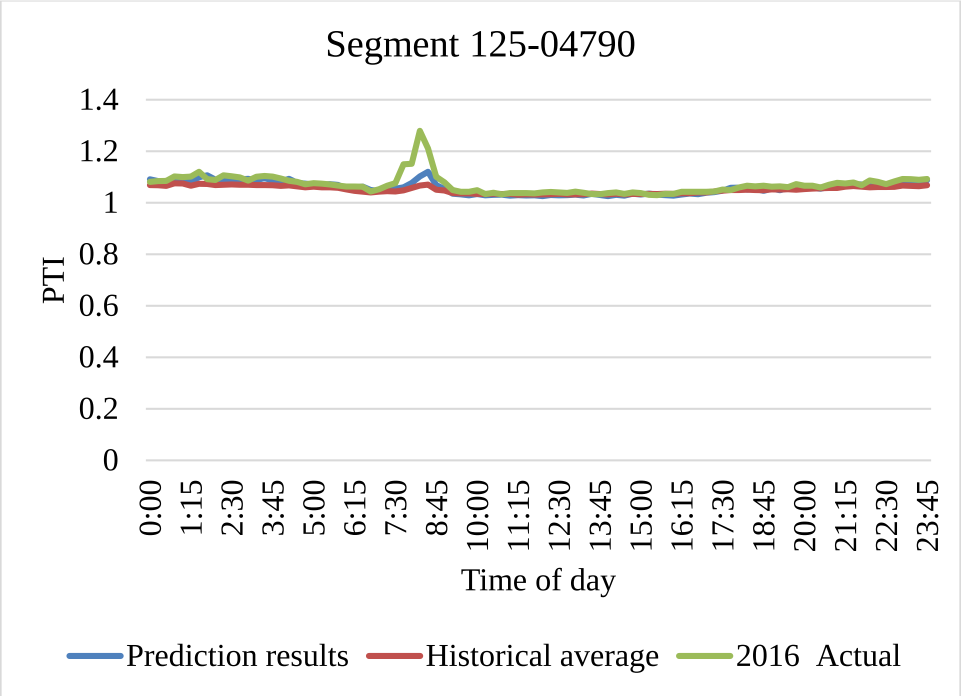

Figure 5.7: Prediction Result of Segment 125-04790

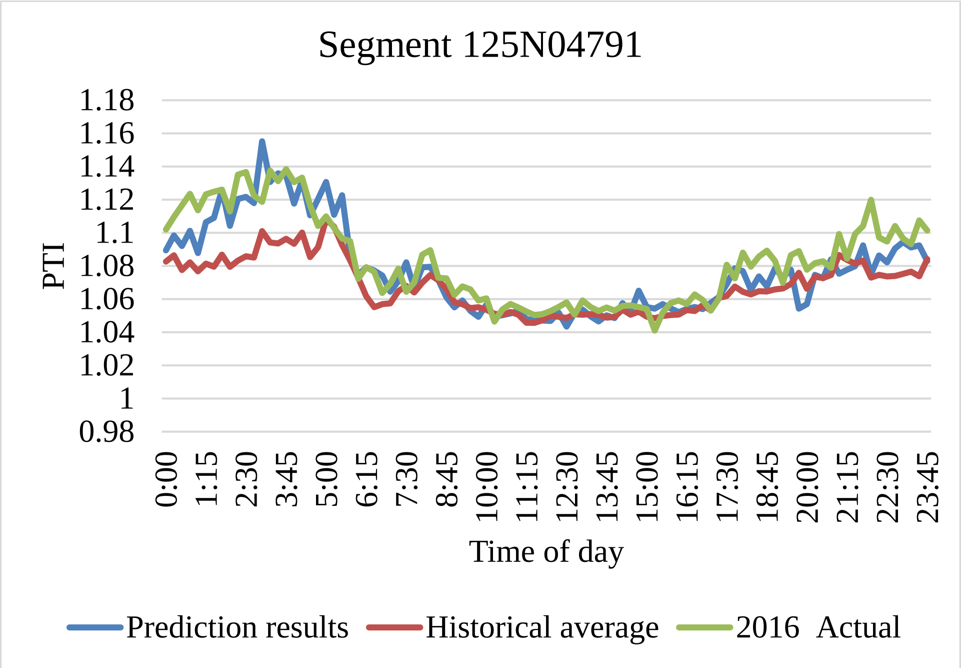

Figure 5.8: Prediction Result of Segment 125N04791

Table 5.1: Percentage Error of Prediction Total Results

Tmc_Code	Study Case	Category	Percentage Error
125-04779	1	total	5.65%
125N04780	1	total	7.50%
125N04788	2	total	7.48%
125-04788	2	total	5.46%
125N04784	3	total	8.27%
125N04785	3	total	18.19%
125-04790	4	total	1.15%
125N04791	4	total	0.90%

5.3.2 TTR Prediction Results Considering DOW

Figure 5.9 to Figure 5.12 below show the comparison of the prediction results with the consideration of DOW, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125-04779 and segment 125N04780, respectively. The result in Table 5.2 shows: for the segments with PM peak characteristics, the prediction model can provide reliable prediction results on weekdays with the errors being 5.19% and 8.23%, respectively. The prediction model can also provide reliable prediction results on weekends with the errors being 4.16% and 4.67%, respectively. The prediction errors on weekends are lower than those on weekdays, which could be explained by lower traffic volume and lower TTR variability on weekends.

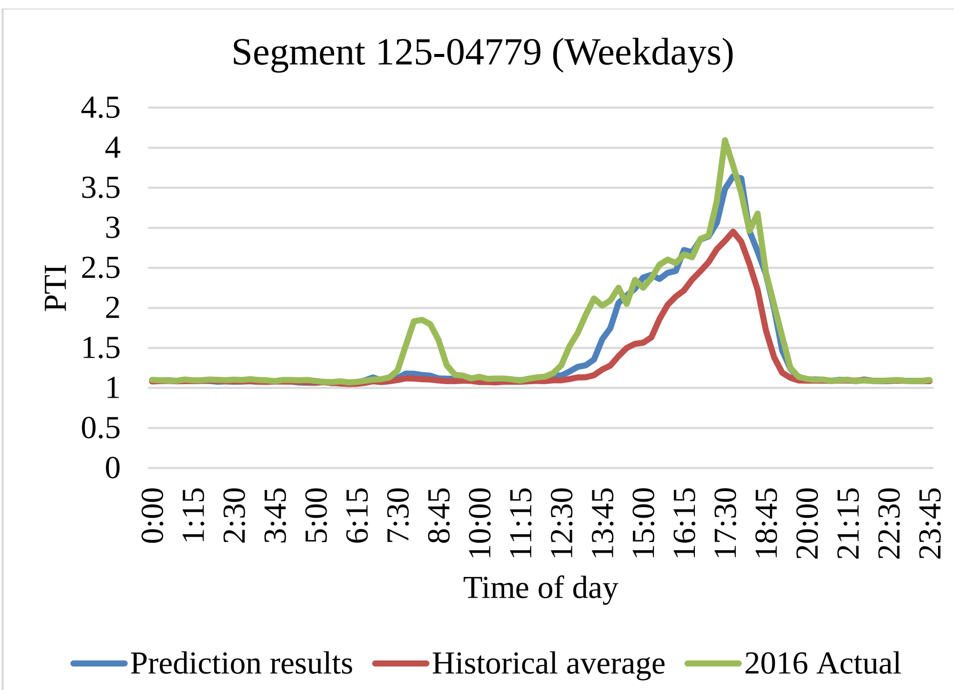

Figure 5.9: Prediction Result of Segment 125-04779 (Weekdays)

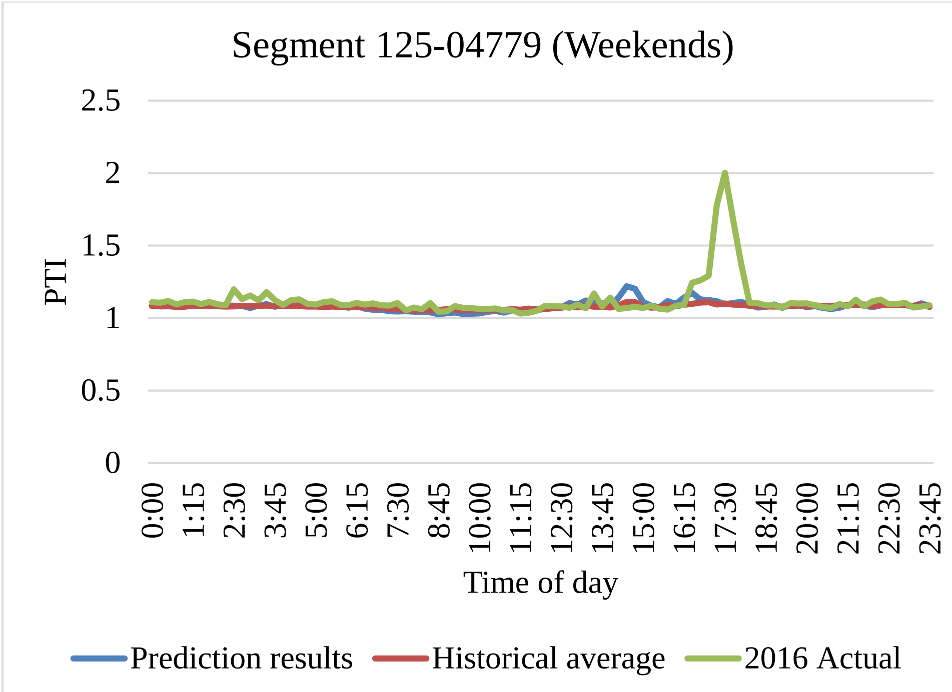

Figure 5.10: Prediction Result of Segment 125-04779 (Weekends)

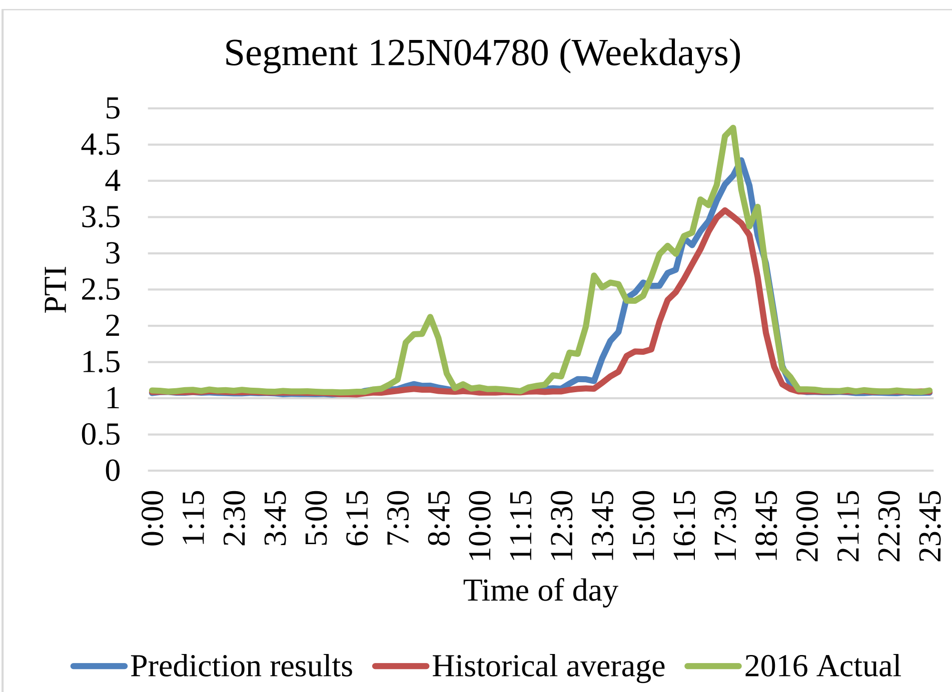

Figure 5.11: Prediction Result of Segment 125N04780 (Weekdays)

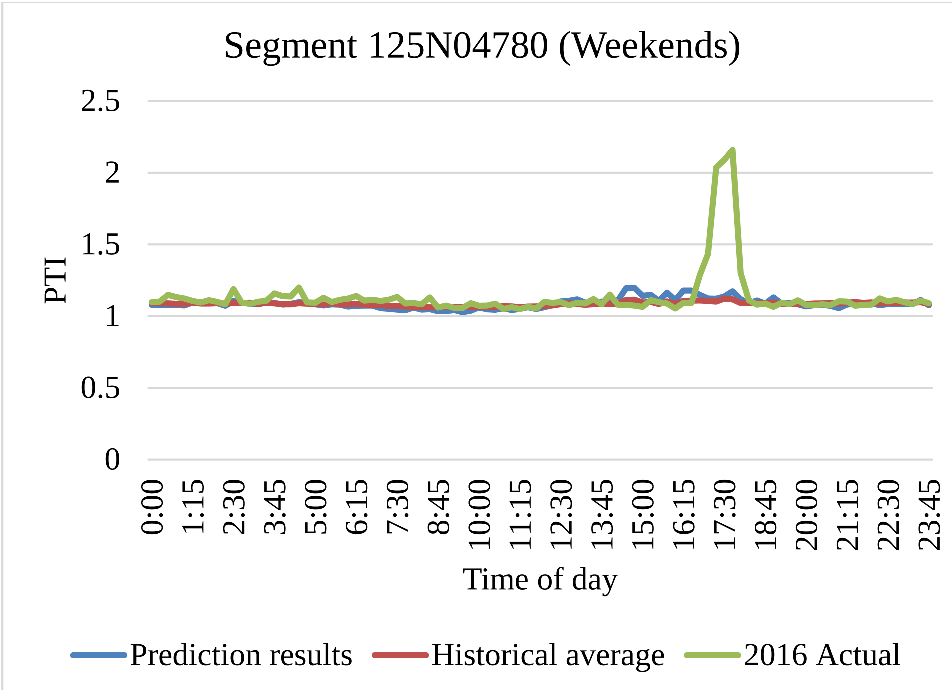

Figure 5.12: Prediction Result of Segment 125N04780 (Weekends)

Figure 5.13 to Figure 5.16 below show the comparison of the prediction results with the consideration of DOW, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125N04788 and segment 125-04788, respectively. The result in Table 5.2 shows: for the segments with AM peak characteristics, the prediction model can provide reliable prediction results on weekdays with the errors being 8.08% and 5.43%, respectively. The prediction model can also provide reliable prediction results on weekends with the errors being 3.05% and 2.53%, respectively. The prediction errors on weekends are lower than those on weekdays, which could also be explained by lower traffic volume and lower TTR variability on weekends.

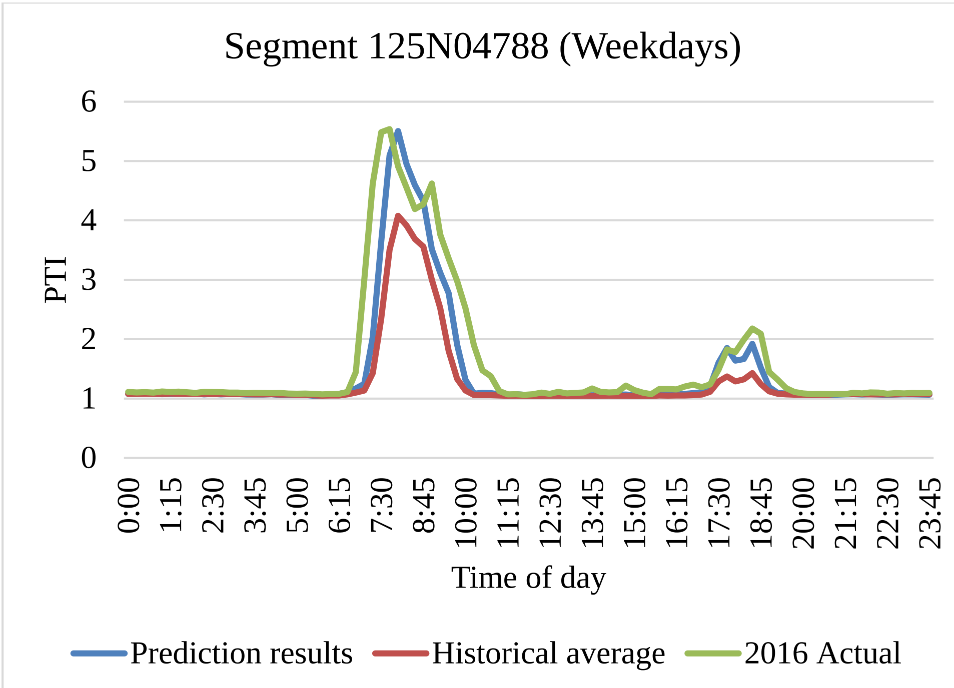

Figure 5.13: Prediction Result of Segment 125N04788 (Weekdays)

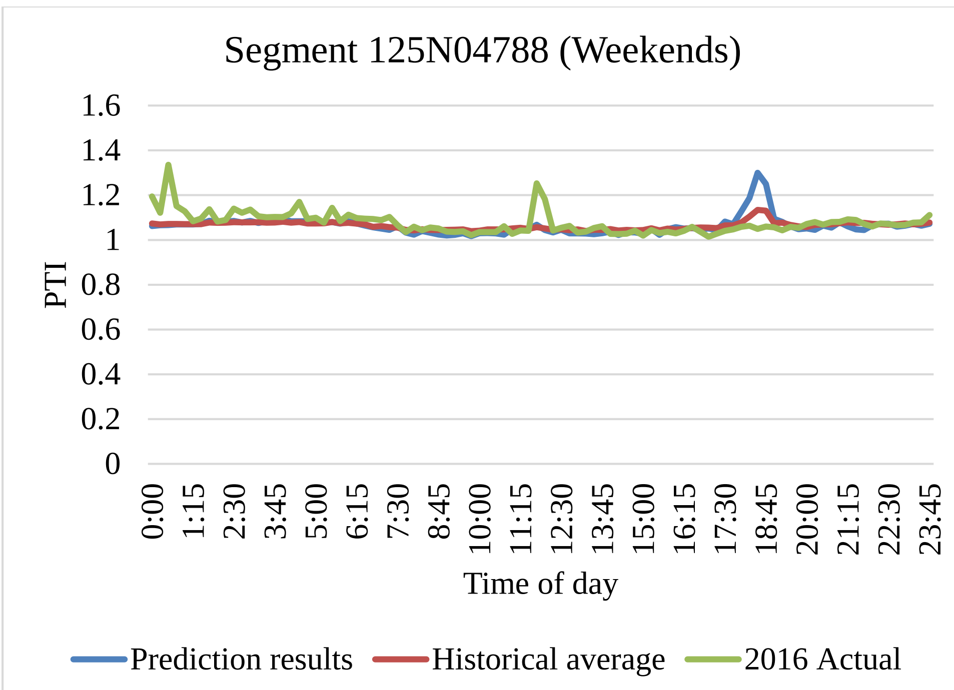

Figure 5.14: Prediction Result of Segment 125N04788 (Weekdays)

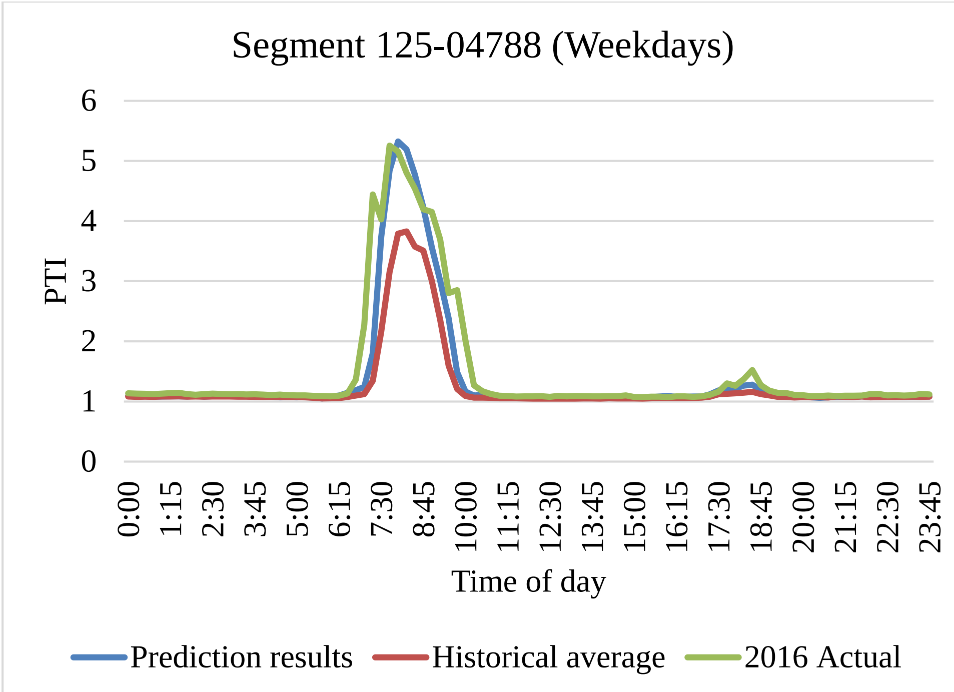

Figure 5.15: Prediction Result of Segment 125-04788 (Weekdays)

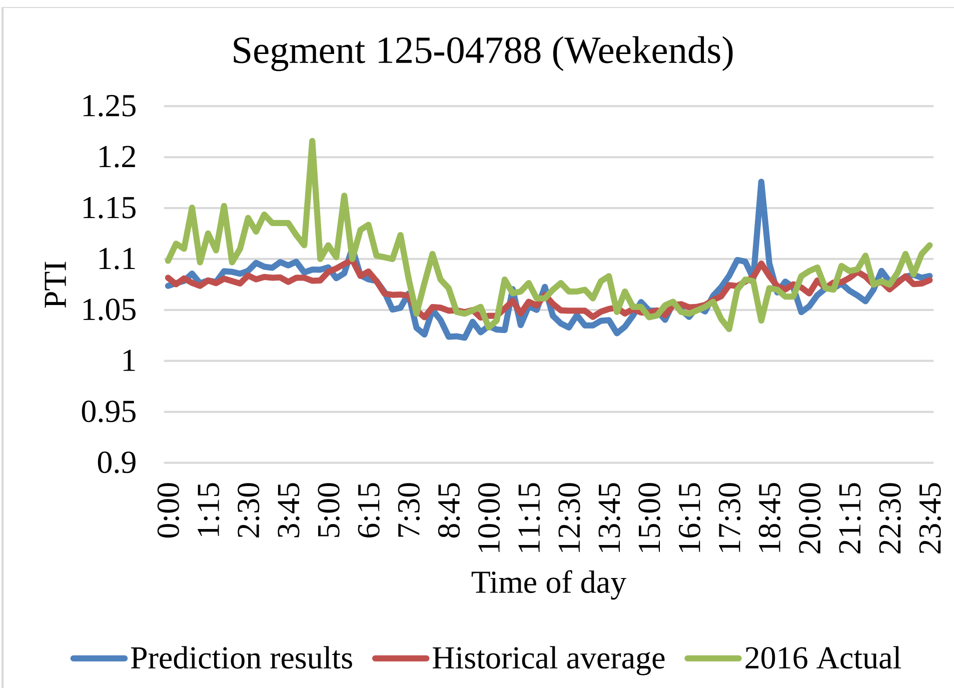

Figure 5.16: Prediction Result of Segment 125-04788 (Weekends)

Figure 5.17 to Figure 5.20 below show the comparison of the prediction results with the consideration of DOW, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125N04784 and segment 125N04785, respectively. The result in Table 5.2 shows: for the segments with double peak characteristics, the prediction model can provide predictions results on weekdays with the errors being 9.34% and 15.74%, respectively. The prediction model can also provide reliable prediction results on weekends with the errors being 9.23% and 6.32%, respectively. The prediction errors on weekends are lower than those on weekdays, which could also be explained by lower traffic volume and lower TTR variability on weekends.

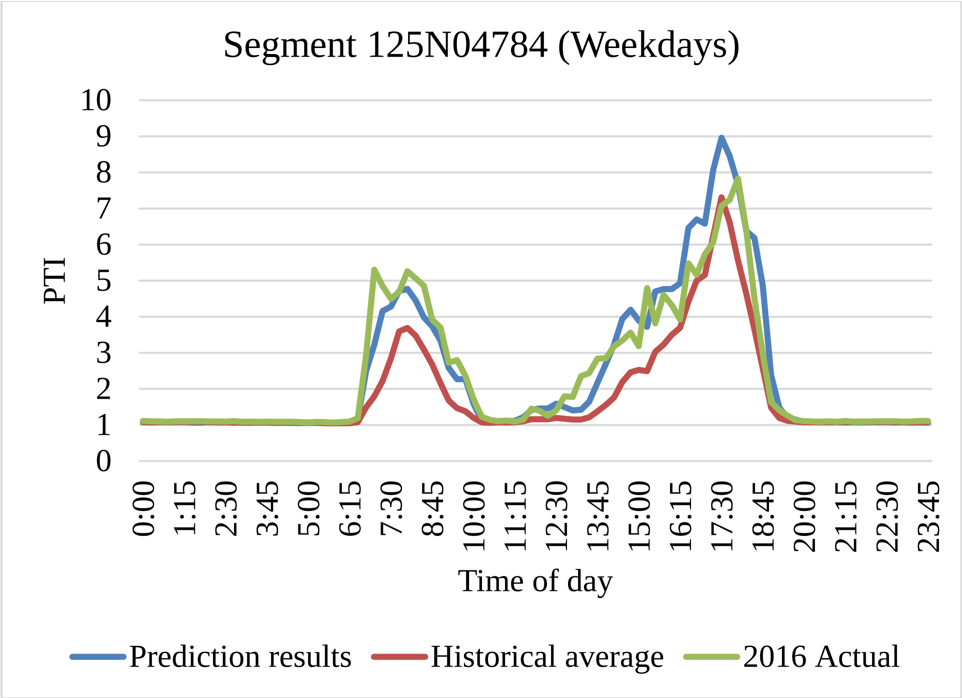

Figure 5.17: Prediction Result of Segment 125N04784 (Weekdays)

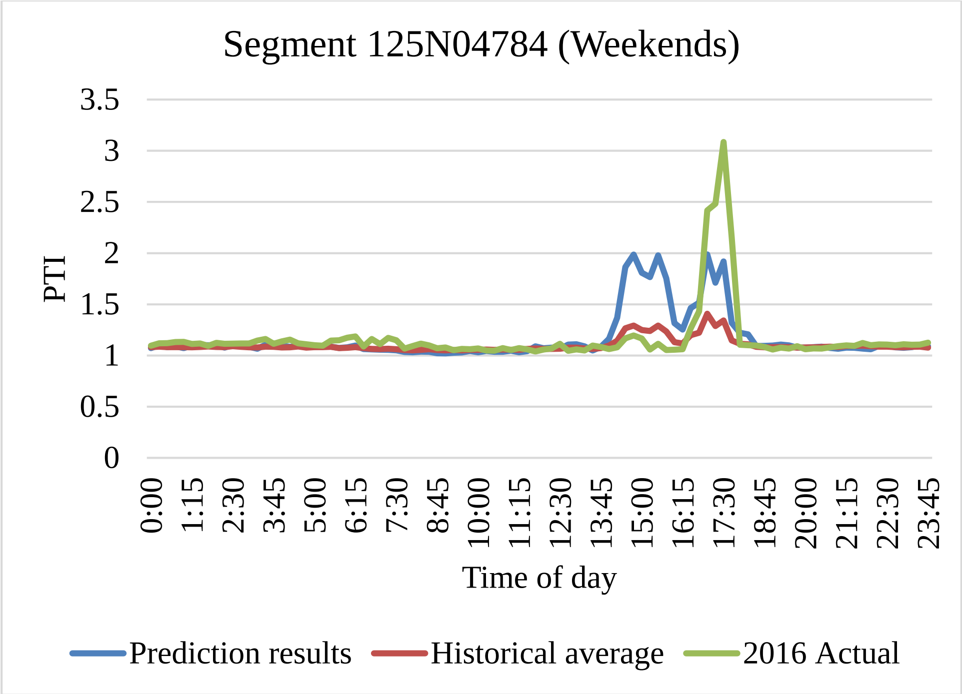

Figure 5.18: Prediction Result of Segment 125N04784 (Weekends)

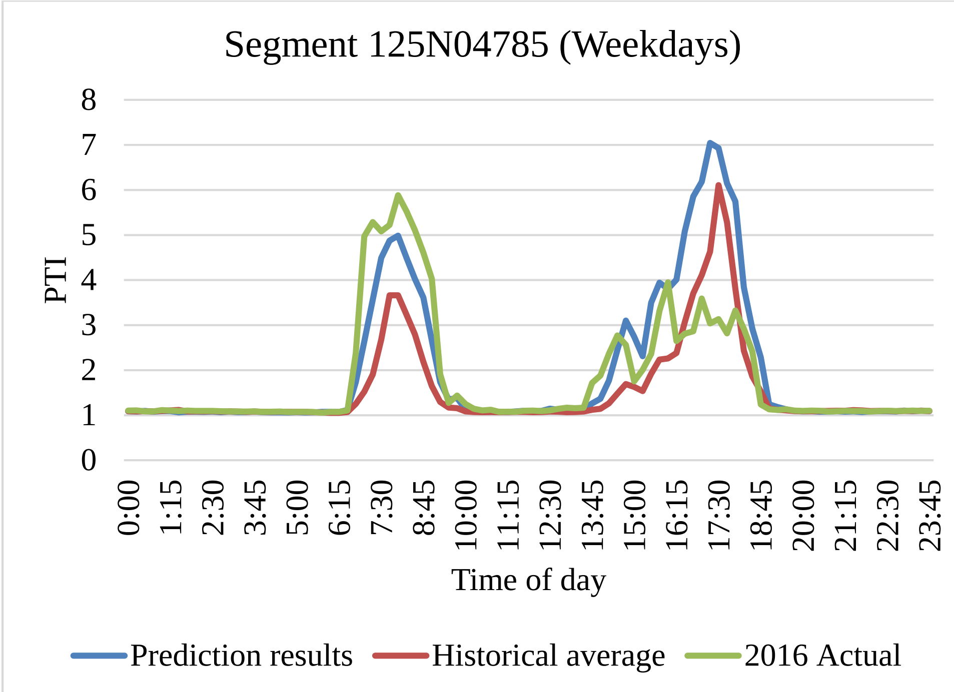

Figure 5.19: Prediction Result of Segment 125N04785 (Weekdays)

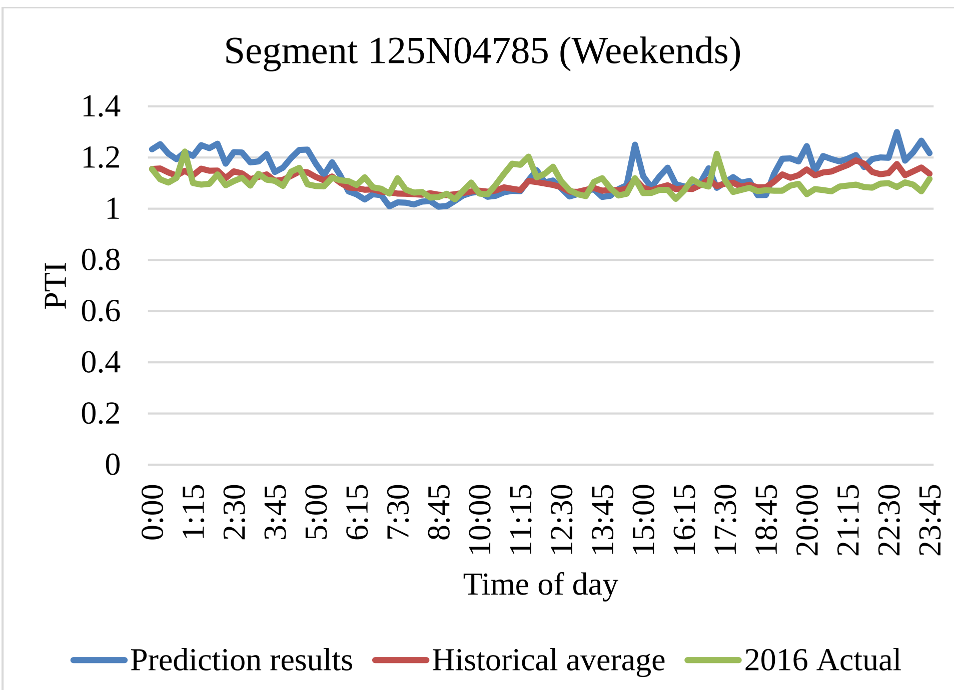

Figure 5.20: Prediction Result of Segment 125N04785 (Weekends)

Figure 5.21 to Figure 5.24 below show the comparison of the prediction results with the consideration of DOW, including the historical average PTIs and the actual PTIs in the year 2016 on segment 125N04784 and segment 125N04785, respectively. The result in Table 5.2

shows: For the segments with no peak characteristics, the prediction model can provide reliable prediction results on weekdays with the errors being 1.21% and 1.01%. The prediction model can also provide reliable prediction results on weekends with the errors being 1.93% and 3.16%. The prediction errors on weekends are higher than those on weekdays, which could be explained by under low traffic volume condition, the larger the sample size, the more accurate the prediction result is.

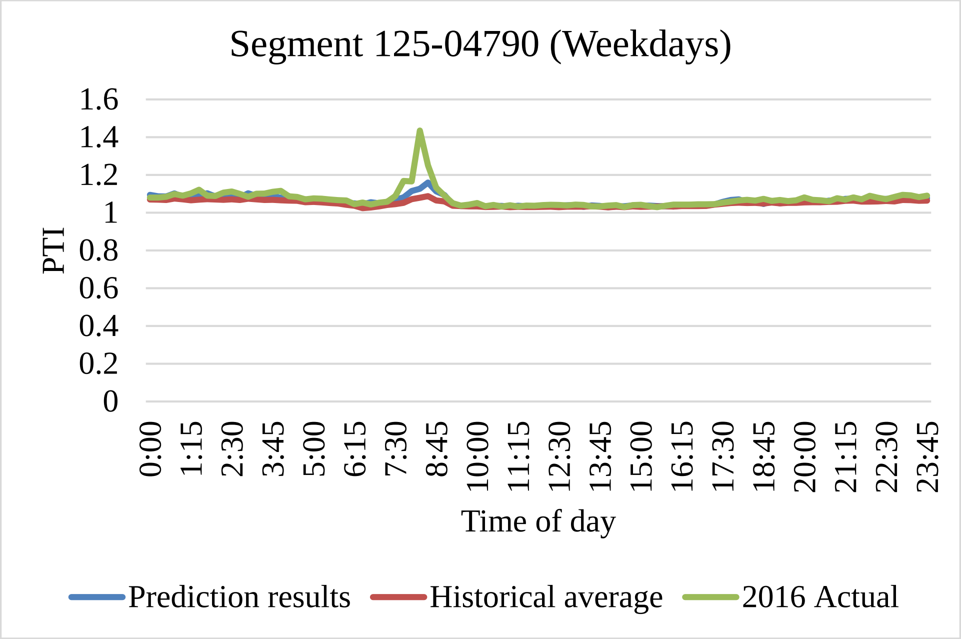

Figure 5.21: Prediction Result of Segment 125-04790 (Weekdays)

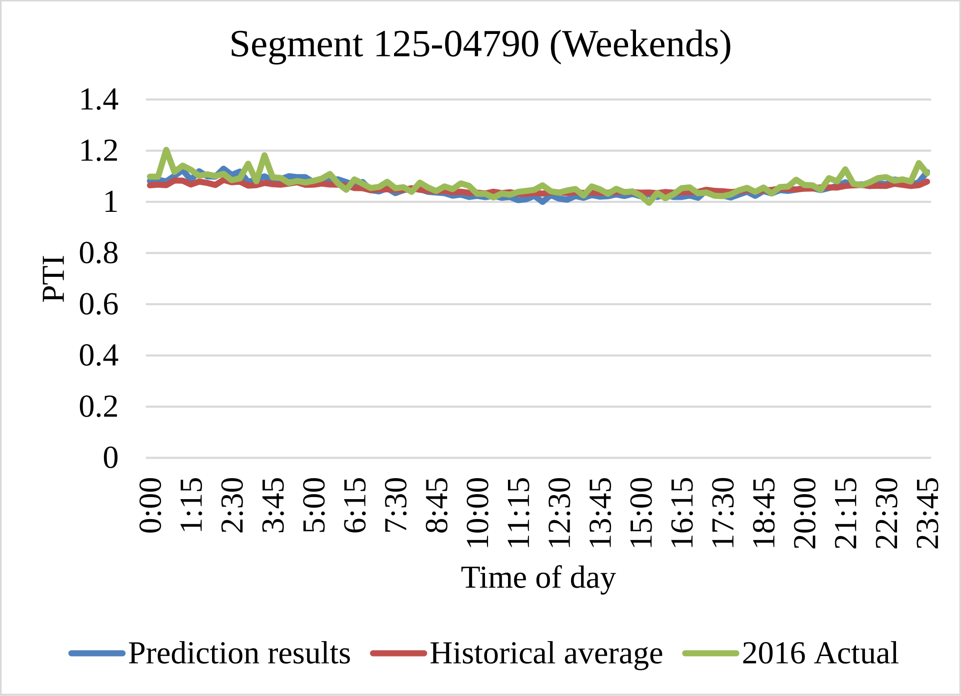

Figure 5.22: Prediction Result of Segment 125-04790 (Weekends)

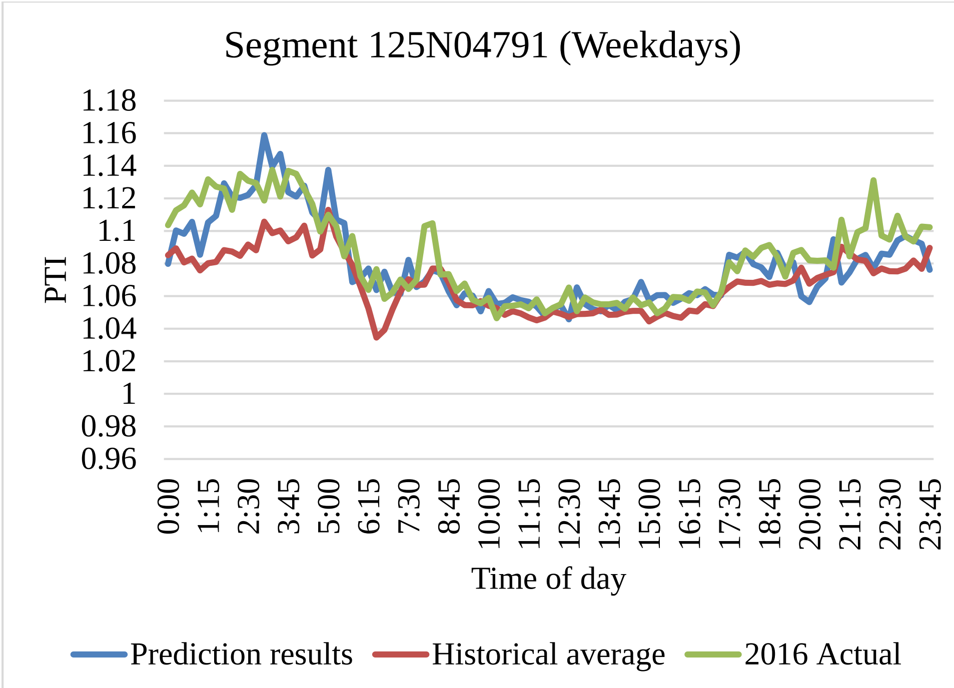

Figure 5.23: Prediction Result of Segment 125N04791 (Weekdays)

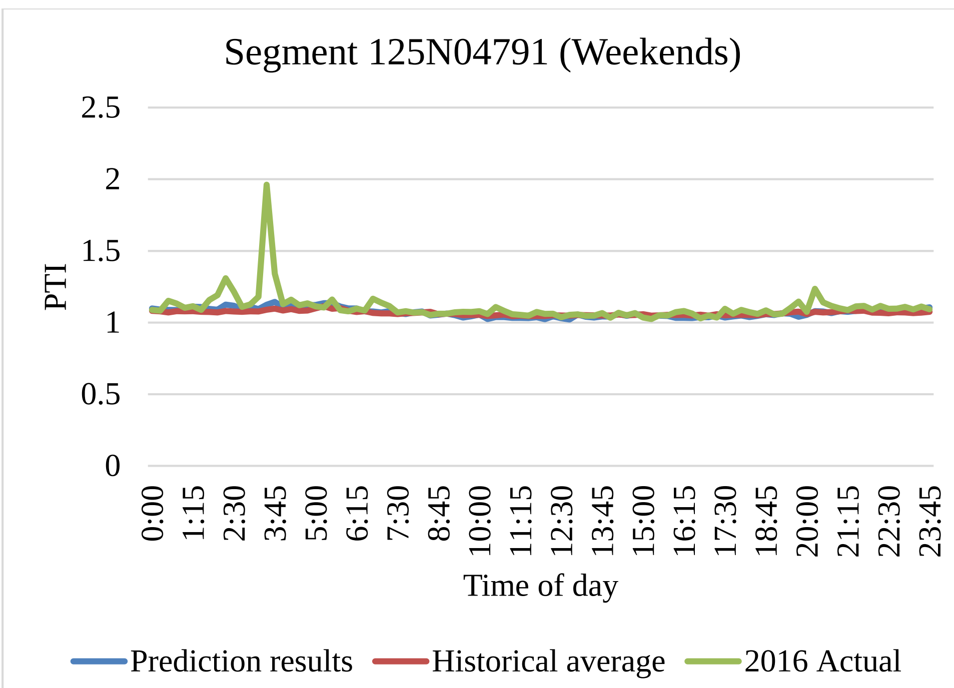

Figure 5.24: Prediction Result of Segment 125N04791 (Weekends)

Table 5.2: Percentage Errors of Prediction Results Considering DOW

Tmc_Code	Study Case	Category	Percentage Error
125-04779	1	weekdays	5.49%
		weekends	4.14%
125N04780	1	weekdays	8.23%
		weekends	4.69%
125N04788	2	weekdays	8.08%
		weekends	3.05%
125-04788	2	weekdays	5.43%
		weekends	2.53%
125N04784	3	weekdays	9.37%
		weekends	9.23%
125N04785	3	weekdays	15.74%
		weekends	6.32%
125-04790	4	weekdays	1.21%
		weekends	1.93%
125N04791	4	weekdays	1.01%
		weekends	3.16%

5.3.3 TTR Prediction Results of Specific DOW

Figures 5.25 and 5.26 below show the comparison of the prediction results from Monday to Sunday and the actual PTIs in the year 2015 on segments 125-04779 and 125N04780, respectively. The result in Table 5.3 shows: for the segments showing PM peak characteristics, the prediction model can provide reliable prediction results of each DOW with the average errors being 8.42% and 8.18%, respectively. The prediction model can provide most reliable prediction results on Monday with the errors being 6.54% and 5.72%, respectively.

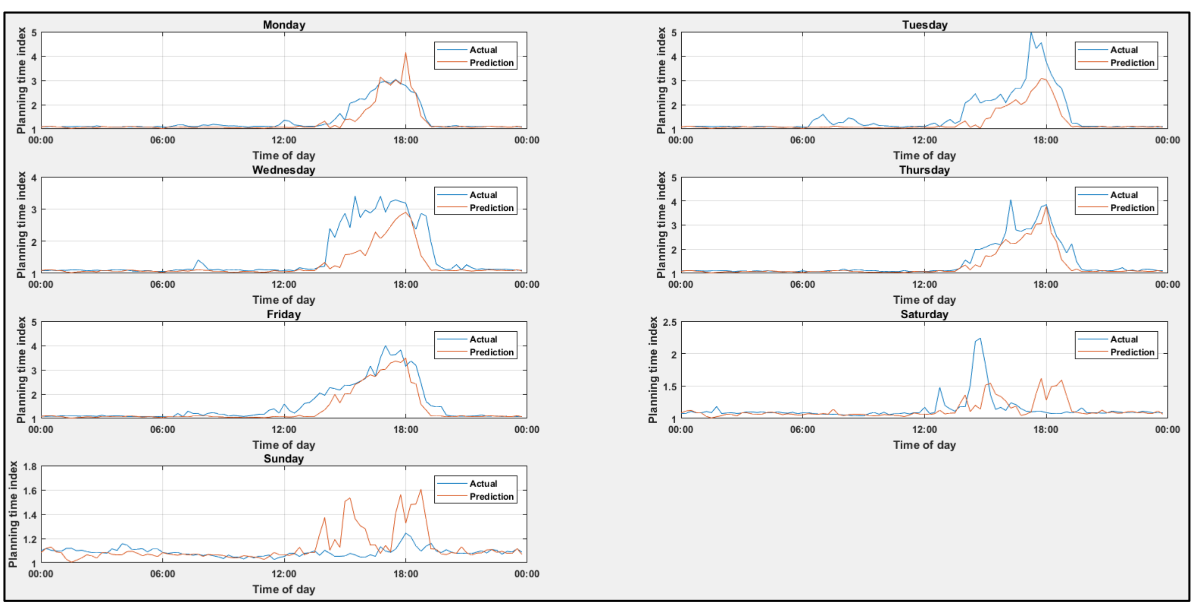

Figure 5.25: Prediction Results of Segment 125-04779 (Monday to Sunday)

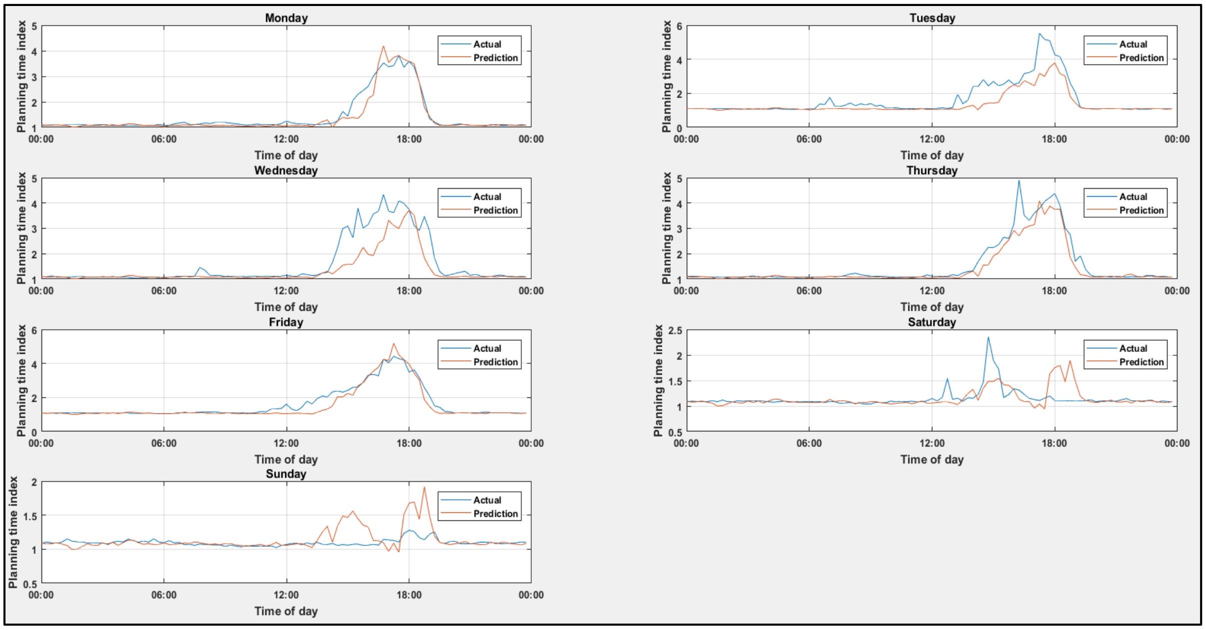

Figure 5.26: Prediction Results of Segment 125N04780 (Monday to Sunday)

Figures 5.27 and 5.28 below show the comparison of the prediction results from Monday to Sunday and the actual PTIs in the year 2015 on segments 125N04788 and 125-04788, respectively. The result in Table 5.3 shows: for the segments showing PM peak characteristics, the prediction model can provide reliable prediction results of each DOW with the average errors being 9.38% and 7.91%, respectively. The prediction model can provide most reliable prediction results on Monday with the errors being 8.07% and 7.55%, respectively.

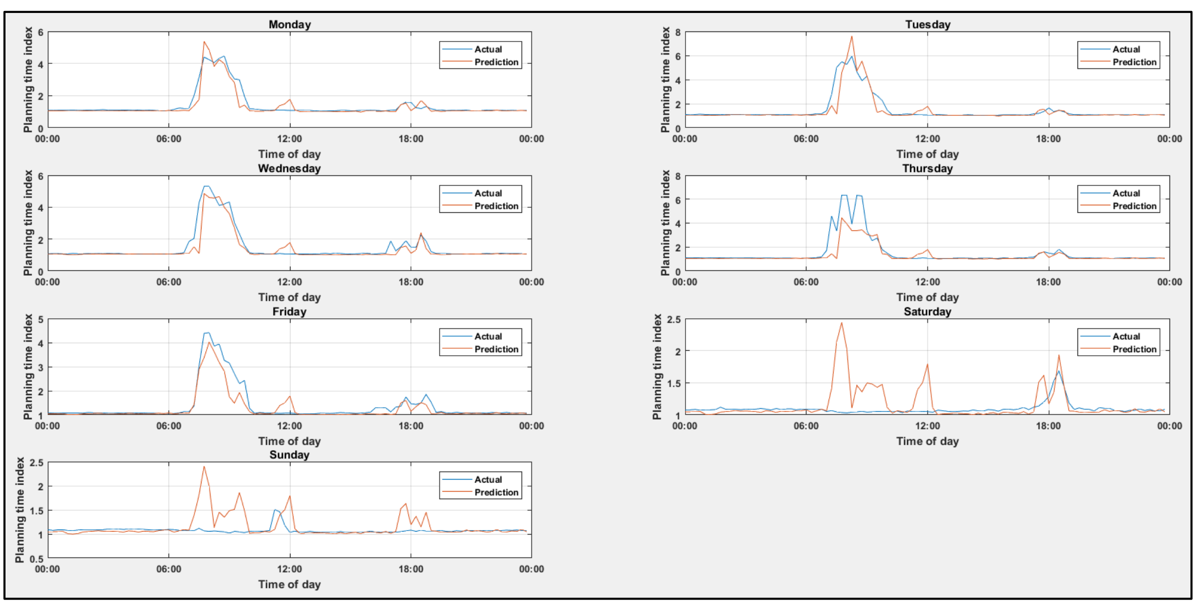

Figure 5.27: Prediction Results of Segment 125N04788 (Monday to Sunday)

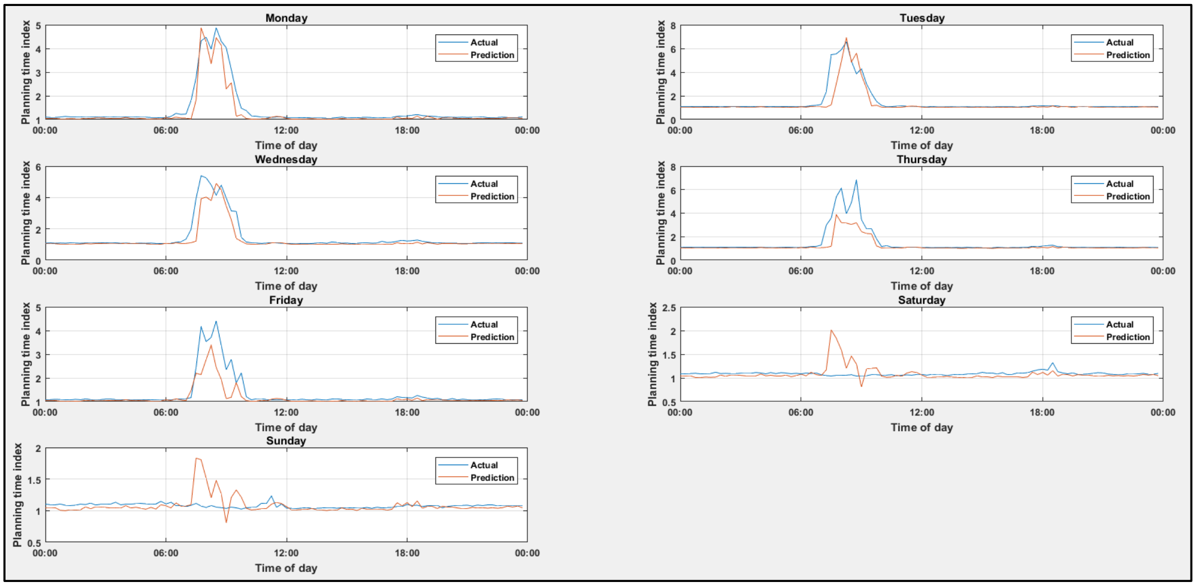

Figure 5.28: Prediction Results of Segment 125-04788 (Monday to Sunday)

Figures 5.29 and 5.30 below show the comparison of the prediction results from Monday to Sunday and the actual PTIs in the year 2015 on segments 125N04784 and 125N04785, respectively. The result in Table 5.3 shows: for the segments showing PM peak characteristics, the prediction model can provide prediction results of each DOW with the average errors being 17.33% and 21.21%, respectively. The prediction model can provide most reliable prediction results on Monday with the errors being 11.52% and 18.06%, respectively.

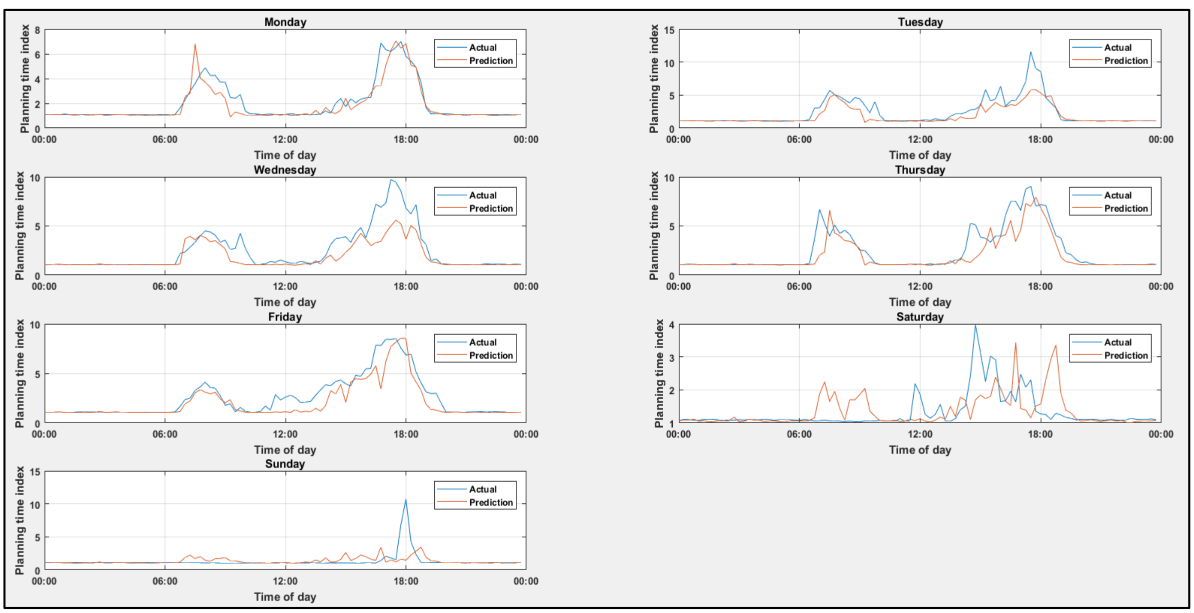

Figure 5.29: Prediction Results of Segment 125N04784 (Monday to Sunday)

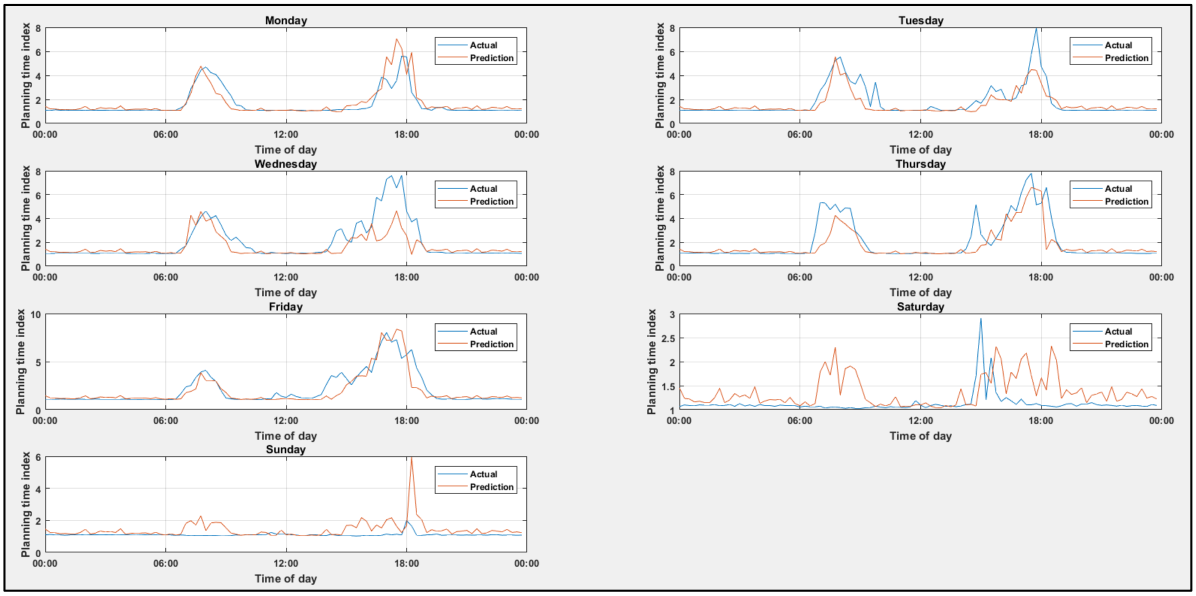

Figure 5.30: Prediction Results of Segment 125N04785 (Monday to Sunday)

Figures 5.31 and 5.32 below show the comparison of the prediction results from Monday to Sunday and the actual PTIs in the year 2015 on segments 125-04790 and 125N04791, respectively. The result in Table 5.3 shows: for the segments showing PM peak characteristics, the prediction model can provide prediction results of each DOW with the average errors being 2.83% and 2.73%, respectively. The prediction model can provide most reliable prediction results on Sunday with the errors being 2.20% and 2.24%, respectively.

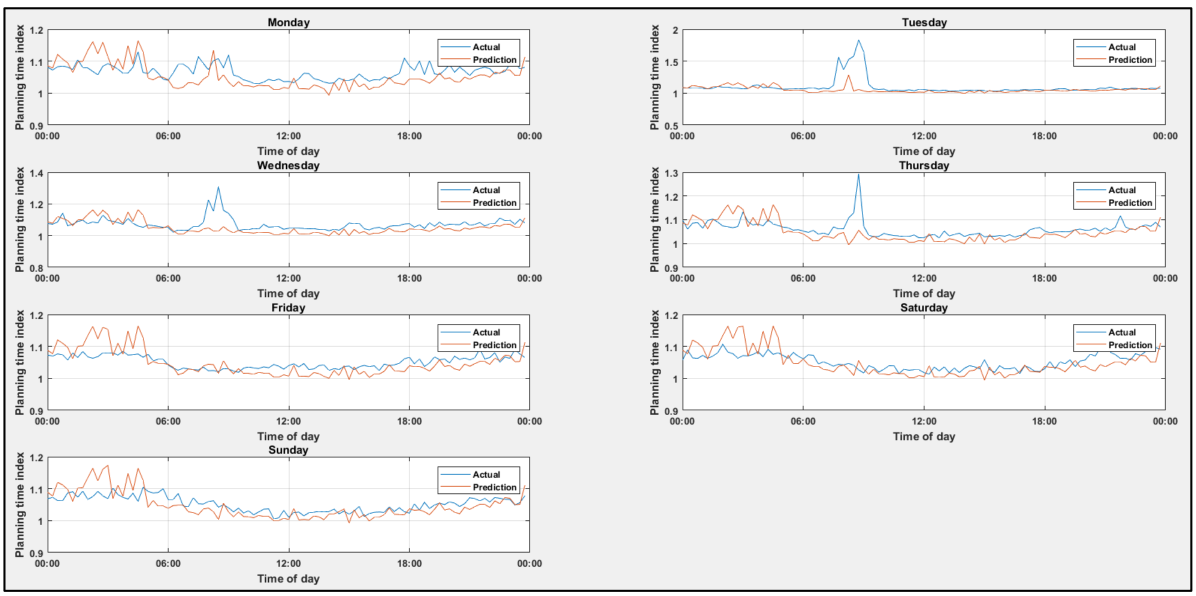

Figure 5.31: Prediction Results of Segment 125-04790 (Monday to Sunday)

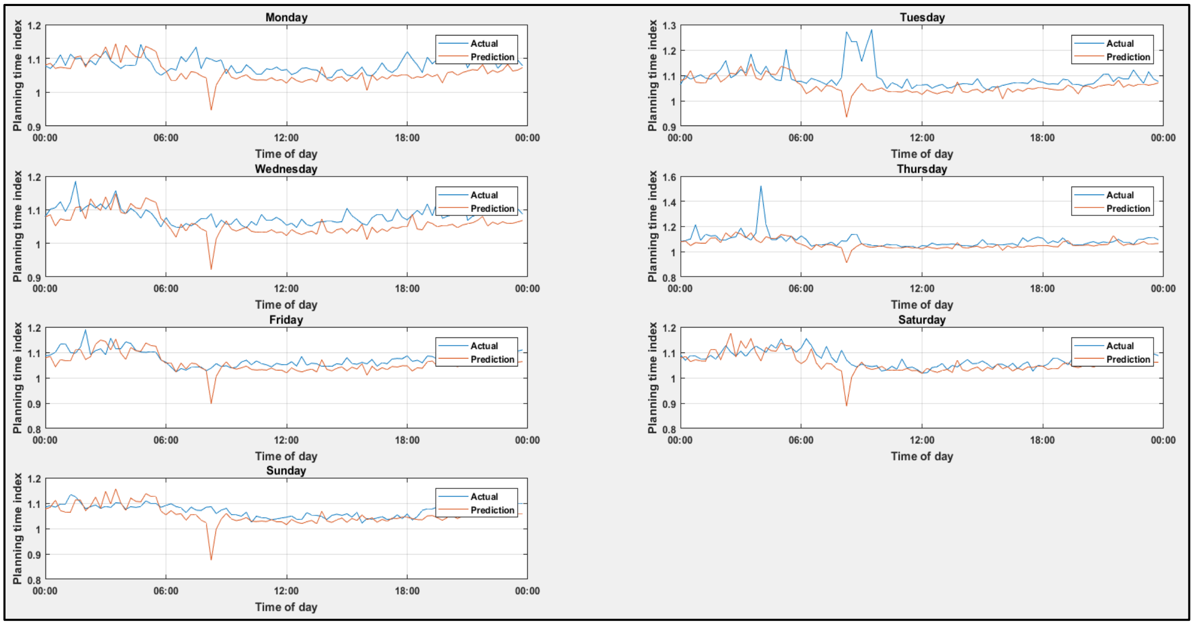

Figure 5.32: Prediction Results of Segment 125N04791 (Monday to Sunday)

Table 5.3: Percentage Errors of Prediction Results (Monday to Sunday)

Segment	**Study Case**	**Average Percentage Error**							
		Mon	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**	**Average**
125-04779	1	6.54%	11.67%	10.61%	6.95%	9.89%	7.13%	6.18%	8.42%
125N04780	1	5.72%	11.57%	10.41%	6.31%	8.26%	7.68%	7.33%	8.18%
125N04788	2	8.07%	8.54%	8.36%	9.21%	8.22%	11.75%	11.48%	9.38%
125-04788	2	7.55%	7.69%	8.38%	8.83%	8.15%	7.95%	6.83%	7.91%
125N04784	3	11.52%	14.68%	16.46%	14.64%	16.37%	22.59%	25.05%	17.33%
125N04785	3	18.06%	18.53%	20.46%	18.53%	18.49%	25.52%	28.86%	21.21%
125-04790	4	2.77%	4.40%	3.29%	2.56%	2.26%	2.32%	2.20%	2.83%
125N04791	4	2.84%	3.30%	2.88%	3.08%	2.40%	2.39%	2.24%	2.73%

5.3.4 TTR Prediction Results of Each Month

Figures 5.33 and 5.34 below show the prediction results of each month and the actual PTIs in the year 2015 on segments 125-04779 and 125N04780, respectively. The result in Table 5.4 shows: for the segments showing PM peak characteristics, the prediction model can provide reliable prediction results with the average errors being 7.68% and 8.83%, respectively. The prediction model can provide most reliable prediction results on April with the errors being 3.90% and 7.03%, respectively.

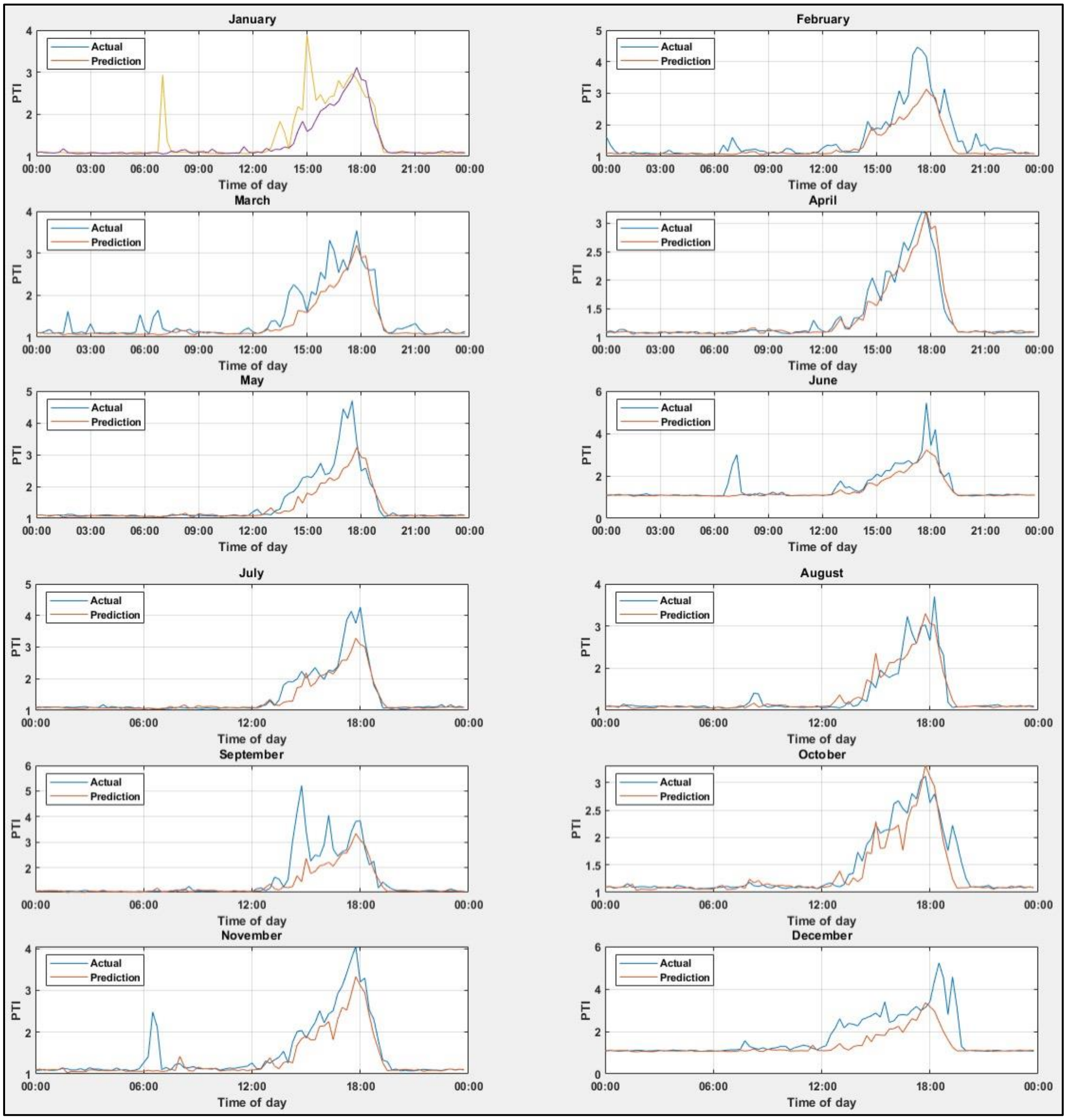

Figure 5.33: Prediction Results of Segment 125-04779 (January to December)

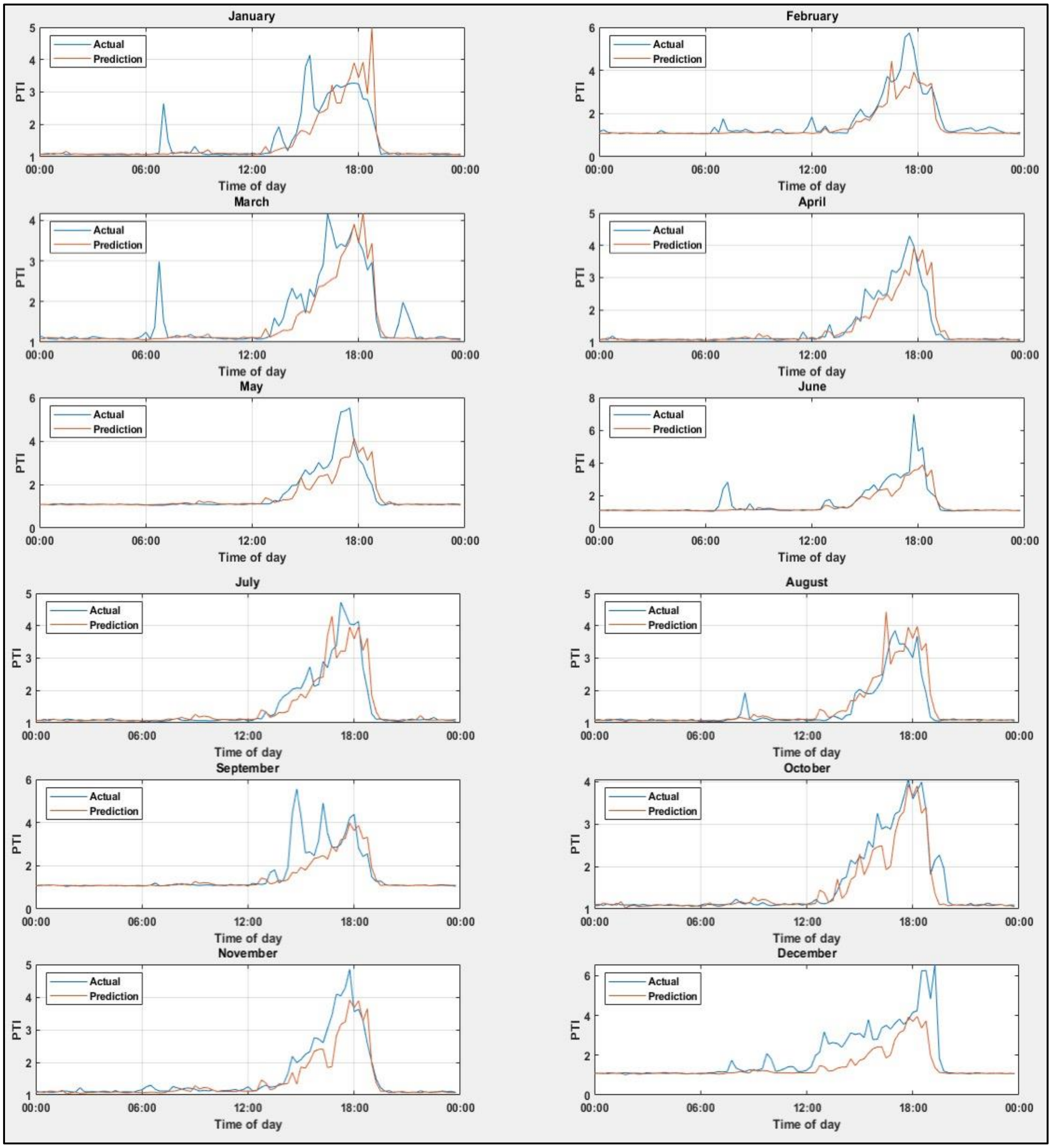

Figure 5.34: Prediction Results of Segment 125N04780 (January to December)

Figures 5.35 and 5.36 below show the prediction results of each month and the actual PTIs in the year 2015 on segments 125N04788 and 125-04788, respectively. The result in Table 5.4 shows: for the segments showing AM peak characteristics, the prediction model can provide reliable prediction results with the average errors being 8.07% and 7.29%, respectively. The prediction model can provide most reliable prediction results on June with the errors being 5.67% and 4.99%, respectively.

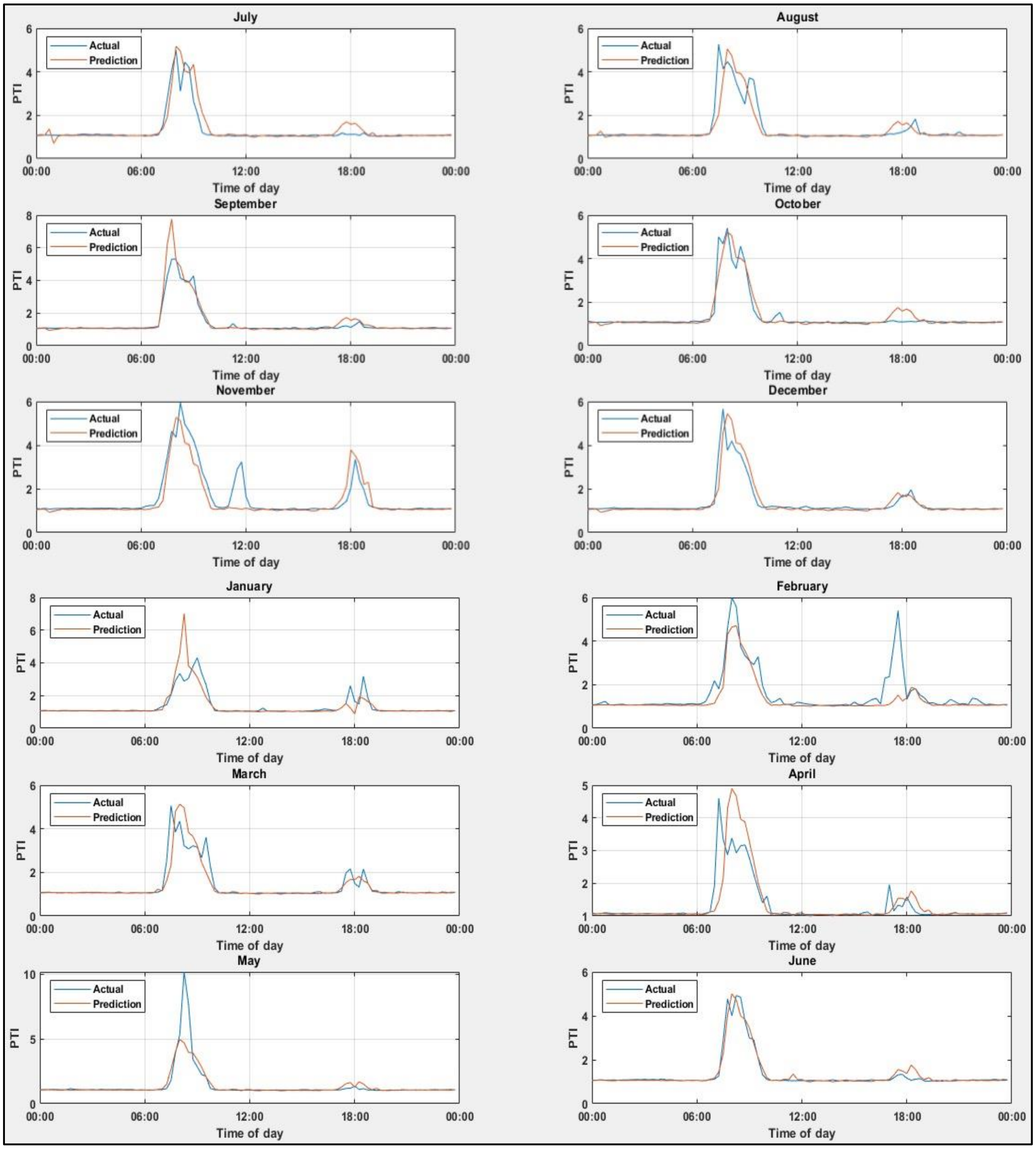

Figure 5.35: Prediction Results of Segment 125N04788 (January to December)

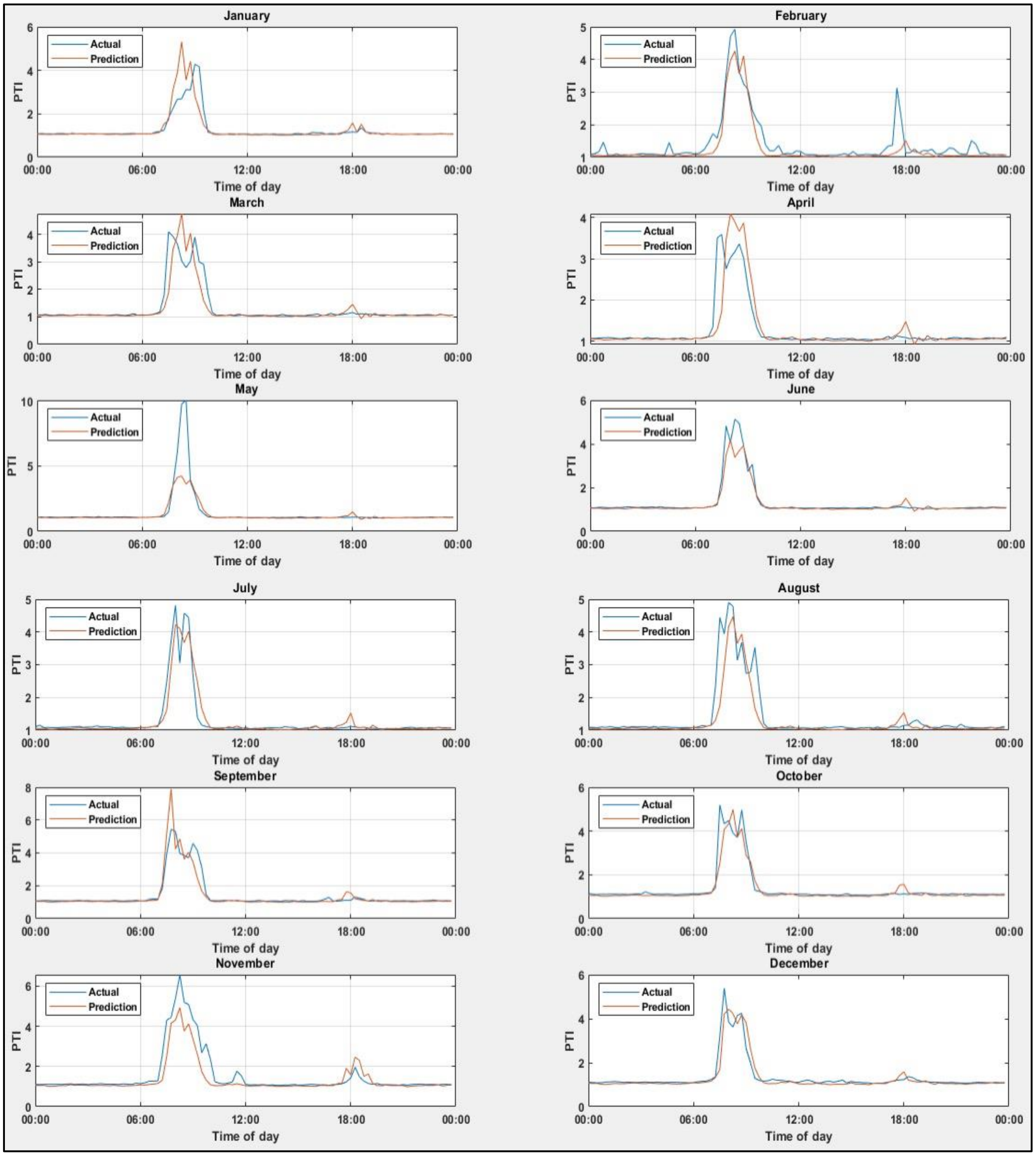

Figure 5.36: Prediction Results of Segment 125-04788 (January to December)

Figures 5.37 and 5.38 below show the prediction results of each month and the actual PTIs in the year 2015 on segments 125N04784 and 125N04785, respectively. The result in Table 5.4 shows: for the segments showing double peak characteristics, the prediction model can provide prediction results with the average errors being 16.10% and 17.94%, respectively. The prediction model can provide most reliable prediction results on May with the errors being 13.03% and 13.44%, respectively.

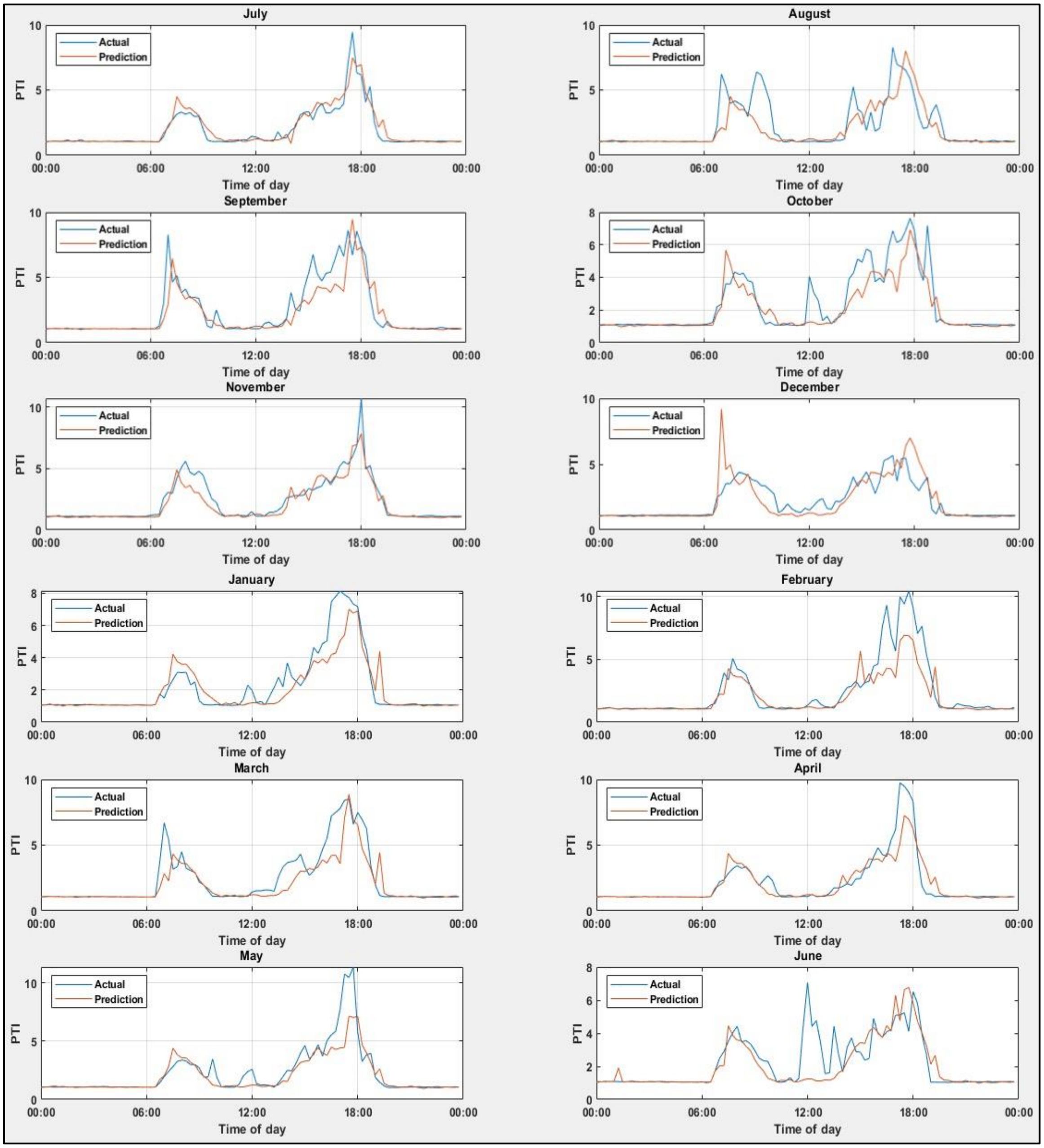

Figure 5.37: Prediction Results of Segment 125N04784 (January to December)

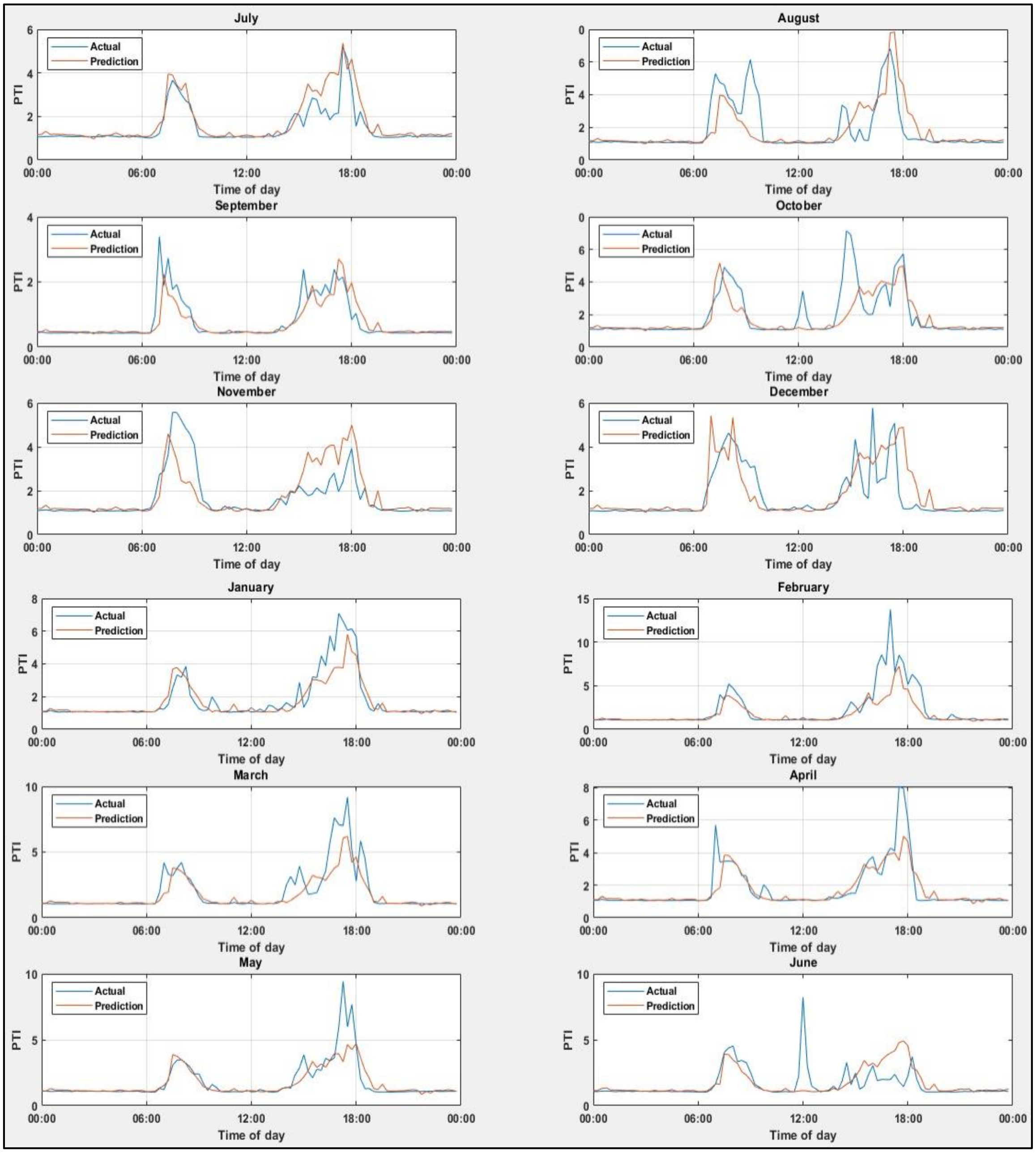

Figure 5.38: Prediction Results of Segment 125-04785 (January to December)

Figures 5.39 and 5.40 below show the prediction results of each month and the actual PTIs in the year 2015 on segments 125-04790 and 125N04791, respectively. The result in Table 5.4 shows: for the segments showing no peak characteristics, the prediction model can provide reliable prediction results with the average errors being 2.77% and 3.15%, respectively. The prediction model can provide most reliable prediction results on March with the errors being 1.85% and 2.15%, respectively.

Figure 5.39: Prediction Results of Segment 125-04790 (January to December)

Figure 5.40: Prediction Results of Segment 125N04791 (January to December)

Table 5.4: Percentage Errors of Prediction Results (January to December)

Segment	Study Case	Average Percentage Error												
		1	2	3	4	5	6	7	8	9	10	11	12	Average
125-04779	1	6.87%	10.67%	8.15%	3.90%	7.28%	7.31%	5.61%	6.07%	8.49%	6.06%	7.53%	14.23%	7.68%
125N04780	1	8.19%	9.67%	8.73%	7.03%	9.03%	8.54%	7.96%	8.24%	8.90%	7.14%	7.16%	15.37%	8.83%
125N04788	2	7.69%	11.04%	6.25%	8.00%	7.10%	5.67%	9.16%	7.76%	6.83%	8.36%	11.28%	7.64%	8.07%
125-04788	2	6.41%	9.93%	6.20%	6.47%	6.38%	4.99%	6.30%	7.22%	7.40%	6.92%	11.42%	7.81%	7.29%
125N04784	3	17.92%	16.72%	15.86%	14.09%	13.03%	17.84%	12.56%	19.04%	15.90%	16.49%	12.11%	21.66%	16.10%
125N04785	3	14.08%	14.57%	14.69%	12.84%	13.44%	24.64%	16.19%	25.41%	16.02%	17.87%	20.27%	25.21%	17.94%
125-04790	4	1.79%	5.64%	1.85%	2.15%	2.65%	1.70%	2.01%	1.82%	4.54%	2.37%	3.88%	2.84%	2.77%
125N04791	4	2.68%	5.81%	2.15%	2.48%	2.16%	2.36%	2.49%	2.31%	4.56%	3.42%	3.77%	3.63%	3.15%

5.4 Summary

This chapter describes the TTR prediction methodology based on the long-term historical TTR data. The following conclusions can be made: The prediction performs best under no peak (low traffic volume) condition and has highest error rates under the double-peak condition. In most cases, the prediction results on weekends are better than the prediction results on weekdays.

Chapter 6. Summary

6.1 Introduction

The chapter summarizes the results achieved in this study. The following sections are organized as follows. Section 6.2 describes the summary of the key results. Section 6.3 concludes this chapter with the discussion of future research directions.

6.2 Summary of Key Results

With the analysis of the TTR of eight typical segments on the I-77 southbound corridor in Charlotte, NC, the TTR variability patterns could be identified under different conditions. Based on the historical TTR data collected in five years (2011 to 2015), the TTR in the year 2016 is predicted, the TTR of specific DOW and the TTR of each month in the year 2015 are also predicted. The information gathered out of this study can be concluded as follows.

In general, the TTR variability patterns of different segments along the corridor are different. Different cases including PM peak only, AM peak only, double-peak and no peak should be analyzed separately since they demonstrate different results. The TTR prediction result also indicates the TTR of a year could be predicted accurately based on the long-term historical TTR data.

With respect to DOW, the TTR analysis results show that for the segments with noticeable peak hour trend, the TTR on weekends are much lower than that on weekdays. The TTR prediction results also show that the prediction errors on weekends are lower than those on weekdays. For the segments with no peak hour, the TTR on weekends are similar to those on weekdays. The TTR prediction results show that the prediction errors on weekends are a little higher than those on weekdays. In particular, for the segments under cases 1 and 3 (PM peak only and double peak, respectively), the TTR on Friday is the highest. For the segments under case 2 (AM peak only), the TTR on Tuesday is the highest. For the segments under case 4 (no peak hour), the TTR on each DOW does not significantly change.

With respect to weather conditions, the TTR analysis results show that the PTIs under rain condition have obviously higher values than those under normal condition throughout the day. The PTIs under snow/ice/fog condition are also higher than the PTIs under normal condition throughout the day with unique variability patterns.

6.3 Conclusions and Future Research Directions

In most cases, TTR data are analyzed at the segment level in the short-term, which may not be able to account for the TTR variability characteristics for the whole section in the long-term. This project aims to develop a systematic approach to analyzing TTR of roadway segments with different variability patterns along a corridor in the long-term. In this project, a number of influential factors are considered when analyzing TTR, including time of day, day of week, year, segment location and weather. A simple linear regression model and a time-series model are developed and used to predict the TTR on a freeway corridor, and acceptable results are achieved.

The methodology and results of this study can be helpful for the TTR modeling related work in the real world. However, with the limited amount of data, the impacts of accidents and roadworks on TTR are not discussed in this study. In the future, the impacts of these variables will be studied if the data can be made available. Spatial relationships between each segment along the corridor and their impacts on the TTR will also be investigated. Furthermore, the TTR analysis will be conducted at a network level and relevant characteristics will be examined in detail.

References

1. Albert, L. P. (2000), Development and validation of an areawide congestion index using Intelligent Transportation Systems data. Doctoral dissertation, Texas A&M University, College Station, Texas.
2. Barkley, T., Hranac, R. and Petty, K. (2012), "Relating Travel Time Reliability and Nonrecurrent Congestion with Multistate Models." *Transportation Research Record: Journal of the Transportation Research Board*, 2278, pp. 13-20.
3. California. (1998), 1998 California Transportation Plan: Transportation System Performance Measures: Final Report. Transportation System Information Program, California Department of Transportation.
4. Cambridge Systematics, Inc. (1998), Multimodal Corridor and Capacity Analysis Manual. NCHRP Report 399, Transportation Research Board of the National Academies, National Research Council, Washington, D.C.
5. Cambridge Systematics, Inc., Dowling Associates, Inc., System Metrics Group, Inc., and Texas Transportation Institute (2008), Cost-Effective Performance Measures for Travel Time Delay, Variation, and Reliability. NCHRP Report 618, Transportation Research Board of the National Academies, Washington, D.C.
6. Cambridge Systematics, Inc., High Street Consulting Group, TransTech Management, Inc., Spy Pond Partners, and Ross & Associates (2009), Performance Measurement Framework for Highway Capacity Decision Making. No. SHRP 2 Report S2-C02-RR, Transportation Research Board of the National Academies, Washington, D.C. Accessed on December 13, 2017,
   Available at: http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_399.pdf.
7. Charles, E. E. (1997), An Introduction to Reliability and Maintainability Engineering. Edition McGraw Hill.
8. Charlotte, C., Helenea, L.M. and Sandra, B. (2017), "Empirical Estimation of the Variability of Travel Time." *Transportation Research Procedia*, 25, pp. 2769-2783.
9. Chen, M., Yu, G., Chen, P., and Wang, Y. (2017), "A Copula-Based Approach for Estimating the Travel Time Reliability of Urban Arterial." *Transportation Research Part C: Emerging Technologies*, 82, pp. 1-23.
10. Chen, P., Tong, R., Lu, G., and Wang, Y. (2018). "Exploring Travel Time Distribution and Variability Patterns Using Probe Vehicle Data: Case Study in Beijing." *Journal of Advanced Transportation*, Article 3747632.
11. Chen, X. M., Chen, X., Zheng, H., and Chen, C. (2017). "Understanding network travel time reliability with on-demand ride service data." *Frontiers of Engineering Management*, 4(4), pp. 388-398.
12. Clark, S. and Watling, D. (2005), "Modelling Network Travel Time Reliability Under Stochastic Demand." *Transportation Research Part B: Methodological*, 39(2), pp. 119-140.
13. Dowling, R. G., Skabardonis, A., Margiotta, R. A. and Hallenbeck, M. E. (2009), "Reliability Breakpoints on Freeways." Transportation Research Board 88th Annual Meeting, Washington D.C., No. 09-0813

14. Elefteriadou, L. and Cui, X. (2007), "A Framework for Defining and Estimating Travel Time Reliability." Transportation Research Board 86th Annual Meeting, Washington D.C., No. 07-1675.
15. Eliasson, J. (2007), "The Relationship Between Travel Time Variability and Road Congestion." 11th World Conference on Transport Research, Berkeley, California.
16. Emam, E., and Ai-Deek, H. (2006), "Using Real-Life Dual-Loop Detector Data to Develop New Methodology for Estimating Freeway Travel Time Reliability." *Transportation Research Record: Journal of the Transportation Research Board*, 1959, pp. 140-150.
17. Fan, W., and Gong, L., (2017), Developing a Systematic Approach to Improving Bottleneck Analysis in North Carolina. North Carolina DOT.
Available at: https://connect.ncdot.gov/projects/research/RNAProjDocs/2016-10%20Final%20Report.pdf
18. Florida Department of Transportation. (2011), The Florida Reliability Method in Florida's Mobility Performance Measures Program.
Available at: http://www.floridampms.com/pdf/trbmpmpaper16.pdf
19. Florida Department of Transportation. (2011). SIS Bottleneck Study (Technical Memorandum No. 2 - Methodology to Identify Bottlenecks).
Available at:
http://www.dot.state.fl.us/planning/systems/programs/mspi/pdf/Tech%20Memo%202.pdf .
20. Gardner Jr, E.S. and McKenzie, E.D. (1985). "Forecasting Trends in Time Series". *Management Science*, 31(10), pp.1237-1246.
21. Guo, F., Rakha, H., and Park, S. (2010), "Multistate Model for Travel Time Reliability." *Transportation Research Record: Journal of the Transportation Research Board*, 2188, pp. 46-54.
22. Hainen, A., Wasson, J., Hubbard, S., Remias, S., Farnsworth, G., and Bullock, D. (2011), "Estimating Route Choice and Travel Time Reliability with Field Observations of Bluetooth Probe Vehicles." *Transportation Research Record: Journal of the Transportation Research Board*, 2256, pp. 43-50.
23. Hojati, A. T., Ferreira, L., Washington, S., Charles, P., and Shobeirinejad, A. (2016), "Modelling the Impact of Traffic Incidents on Travel Time Reliability." *Transportation research part C: emerging technologies*, 65, pp. 49-60.
24. Javid, R. J., and Javid, R. J. (2017), "A Framework for Travel Time Variability Analysis Using Urban Traffic Incident Data." *IATSS Research*, 42(1), pp.30-38.
25. Kamga, C., and Yazıcı, M. A. (2014), "Temporal and Weather-Related Variation Patterns of Urban Travel Time: Considerations and Caveats for Value of Travel Time, Value of Variability, and Mode Choice Studies." *Transportation Research Part C: Emerging Technologies*, 45, pp. 4-16.
26. Kim, J. (2014), Travel Time Reliability of Traffic Networks: Characterization, Modeling and Scenario-based Simulation. Doctoral dissertation, Northwestern University, Evanston, Illinois
27. Kwon, J., Barkley, T., Hranac, R., Petty, K. and Compin, N. (2011), "Decomposition of Travel Time Reliability into Various Sources: Incidents, Weather, Work Zones, Special Events, and Base Capacity." *Transportation Research Record: Journal of the Transportation Research Board*, 2229, pp. 28-33.

28. Lei, F., Wang, Y., Lu, G., and Sun, J. (2014), "A Travel Time Reliability Model of Urban Expressways with Varying Levels of Service." *Transportation Research Part C: Emerging Technologies*, 48, pp. 453-467.
29. Li, Z., Elefteriadou, L. and Kondyli, A. (2016), "Quantifying Weather Impacts on Traffic Operations for Implementation into A Travel Time Reliability Model." *Transportation Letters: The International Journal of Transportation Research*, 8(1), pp. 47-59.
30. Li, Z., Yu, H., Liu, C. and Liu, F. (2008), "An Improved Adaptive Exponential Smoothing Model for Short-Term Travel Time Forecasting of Urban Arterial Street." *Acta Automatica Sinica*, 34(11), pp.1404-1409.
31. Lomax, T., D. Schrank, S. Turner, and R. Margiotta. (2003), Selecting Travel Time Reliability Measures. Texas Transportation Institute. Available at: https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2003-3.pdf.
32. Lomax, T., Turner, S., Shunk, G., Levinson, H. S., Pratt, R. H., Bay, P. N., and Douglas, G. B. (1997), Quantifying Congestion, Volume 1: Final Report. NCHRP Report 398, Transportation Research Board of the National Academies, Washington, D.C. Available at: http://onlinepubs. trb. org/onlinepubs/nchrp/nchrp_rpt_398. pdf.
33. Martchouk, M., Mannering, F., and Bullock, D. (2010), "Analysis of Freeway Travel Time Variability Using Bluetooth Detection." *Journal of Transportation Engineering*, 137(10), pp. 697-704.
34. McLeod, D. S., Elefteriadou, L., and Jin, L. (2012), "Travel Time Reliability as a Performance Measure: Applying Florida's Predictive Model to an Entire Freeway System." *Institute of Transportation Engineers. ITE Journal*, 82(11), pp. 43.
35. Ng, M., and Waller, S. T. (2010), "A Computationally Efficient Methodology to Characterize Travel Time Reliability Using the Fast Fourier Transform." *Transportation Research Part B: Methodological*, 44(10), pp. 1202-1219.
36. North Carolina DMV. (2016), North Carolina 2016 Traffic Crash Facts Available at: https://connect.ncdot.gov/business/DMV/DMV%20Documents/2016%20Crash%20Facts.pdf
37. Peer, S., Koopmans, C. C., and Verhoef, E. T. (2012), "Prediction of Travel Time Variability for Cost-Benefit Analysis." *Transportation Research Part A: Policy and Practice*, 46(1), pp. 79-90.
38. Pu, W. (2011), "Analytic Relationships Between Travel Time Reliability Measures." *Transportation Research Record: Journal of the Transportation Research Board*, 2254, pp. 122-130.
39. Recker, W., Chung, Y., Park, J., Wang, L., Chen, A., Ji, Z. ... and Oh, J. S. (2005), Considering Risk-taking Behavior in Travel Time Reliability. California Partners for Advanced Transit and Highways (PATH). Available at: http://caltrans.ca.gov/newtech/researchreports/2002-2006/2005/to_4110.pdf
40. Saberi, M., and Bertini, R. L. (2010), "Beyond Corridor Reliability Measures: Analysis of Freeway Travel Time Reliability at the Segment Level for Hot Spot Identification." Transportation Research Board 89th Annual Meeting. Washington D.C., US. No. 10-2341.
41. Schrank, D., Eisele, B., Lomax, T., and Bak, J. (2015), 2015 Urban Mobility Scorecard. Texas A&M Transportation Institute, INRIX Inc. Available at: http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-scorecard-2015.pdf.

42. Schroeder, B., Rouphail, N., and Aghdashi, S. (2013), "Deterministic Framework and Methodology for Evaluating Travel Time Reliability on Freeway Facilities." *Transportation Research Record: Journal of the Transportation Research Board*, 2396, pp. 61-70.
43. Shao, H., Lam, W. H., Tam, M. L., and Yuan, X. M. (2008), "Modelling Rain Effects on Risk-Taking Behaviours of Multi-User Classes in Road Networks with Uncertainty." *Journal of Advanced Transportation*, 42(3), pp. 265-290.
44. Sohn, K., and Kim, D. (2009), "Statistical Model for Forecasting Link Travel Time Variability." *Journal of Transportation Engineering*, 135(7), pp. 440-453.
45. Texas Transportation Institute, and Cambridge Systems, Inc. (2010), Travel Time Reliability: Making It There on Time, All the Time. FHWA.
Available at: http://www.ops.fhwa.dot.gov/publications/tt_reliability/TTR_Report.html.
46. Tsapakis, I., Cheng, T., and Bolbol, A. (2013). "Impact of weather conditions on macroscopic urban travel times." *Journal of Transport Geography*, 28, pp. 204-211.
47. Tu, H. (2008), Monitoring Travel Time Reliability on Freeways. Doctoral dissertation, Delft University of Technology, Delft, Netherlands.
48. Tu, H., Li, H., Van Lint, H., Knoop, V., and Sun, L. (2013). "Macroscopic Travel Time Reliability Diagrams for Freeway Networks." *Transportation Research Record: Journal of the Transportation Research Board*, 2396, pp. 19-27.
49. Turner, S. M., Best, M. E., and Schrank, D. L. (1996), Measures of Effectiveness for Major Investment Studies. No. SWUTC/96/467106-1, Transportation Research Board of the National Academies, Washington, D.C.
Available at: http://tti.tamu.edu/documents/467106-1.pdf
50. Van Lint, J. and Van Zuylen, H. (2005), "Monitoring and Predicting Freeway Travel Time Reliability: Using Width and Skew of Day-To-Day Travel Time Distribution." *Transportation Research Record: Journal of the Transportation Research Board*, 191, pp. 54-62.
51. Vandervalk, A., Louch, H., Guerre, J., and Margiotta, R. (2014), Incorporating Reliability Performance Measures into the Transportation Planning and Programming Processes: Technical Reference. No. SHRP 2 Report S2-L05-RR-3, Transportation Research Board of the National Academies, Washington, D.C.
Available at:
https://www.camsys.com/sites/default/files/publications/SHRP2prepubL05Report.pdf.
52. Wang, Z., Goodchild, A., and McCormack, E. (2017), "A Methodology for Forecasting Freeway Travel Time Reliability Using GPS Data." *Transportation Research Procedia*, 25, pp. 842-852.
53. Weng, J., Liu, L., and Rong, J. (2013), "Impacts of snowy weather conditions on expressway traffic flow characteristics." *Discrete dynamics in nature and society*, 2013.
54. Wolniak, M., and Mahapatra, S. (2014), "Data- and Performance-Based Congestion Management Approach for Maryland Highways." *Transportation Research Record: Journal of the Transportation Research Board*, 2420, pp. 23-32.
55. Yang, S. (2016), Estimating Freeway Travel Time Reliability for Traffic Operations and Planning. Doctoral Dissertation, University of Arizona, Tucson, Arizona.
56. Yang, S., Malik, A., and Wu, Y. J. (2014), "Travel Time Reliability Using the Hasofer-Lind-Rackwitz-Fiessler Algorithm and Kernel Density Estimation." *Transportation Research Record: Journal of the Transportation Research Board*, 2442, pp. 85-95.

57. Yazici, M., Kamga, C. and Mouskos, K. (2012), "Analysis of Travel Time Reliability in New York City Based on Day-Of-Week and Time-Of-Day Periods." *Transportation Research Record: Journal of the Transportation Research Board*, 230, pp. 83-95.
58. Zhao, L., and Chien, S. I. J. (2012). Analysis of Weather Impact on Travel Speed and Travel Time Reliability. In CICTP 2012: Multimodal Transportation Systems—Convenient, Safe, Cost-Effective, Efficient.
59. Zheng, F., Li, J., van Zuylen, H., Liu, X., and Yang, H. (2017), "Urban Travel Time Reliability at Different Traffic Conditions." *Journal of Intelligent Transportation Systems*, 22(2), pp. 106-120.

Appendix A: PTIs of Each Segment

TMC Code	Year	Time Period	Average PTI	Rating
125N04776	2011	AM Peak	1.06266	reliable
		PM Peak	1.134655	reliable
	2012	AM Peak	1.040118	reliable
		PM Peak	1.397752	reliable
	2013	AM Peak	1.036858	reliable
		PM Peak	1.59996	unreliable
	2014	AM Peak	1.049939	reliable
		PM Peak	1.901685	unreliable
	2015	AM Peak	1.056985	reliable
		PM Peak	2.262251	unreliable
125-04776	2011	AM Peak	1.046534	reliable
		PM Peak	1.061458	reliable
	2012	AM Peak	1.051751	reliable
		PM Peak	1.162759	reliable
	2013	AM Peak	1.045789	reliable
		PM Peak	1.310971	reliable
	2014	AM Peak	1.076656	reliable
		PM Peak	1.600031	unreliable
	2015	AM Peak	1.075308	reliable
		PM Peak	1.915216	unreliable
125N04777	2011	AM Peak	1.068902	reliable
		PM Peak	1.084726	reliable
	2012	AM Peak	1.043128	reliable
		PM Peak	1.225618	reliable
	2013	AM Peak	1.040042	reliable
		PM Peak	1.393853	reliable
	2014	AM Peak	1.054416	reliable
		PM Peak	1.764437	unreliable
	2015	AM Peak	1.056168	reliable
		PM Peak	2.011691	unreliable
125-04777	2011	AM Peak	1.076099	reliable
		PM Peak	1.104977	reliable
	2012	AM Peak	1.052621	reliable
		PM Peak	1.114886	reliable
	2013	AM Peak	1.052491	reliable
		PM Peak	1.223671	reliable

	2014	AM Peak	1.069147	reliable
		PM Peak	1.447633	reliable
	2015	AM Peak	1.07648	reliable
		PM Peak	1.515755	unreliable
125N04778	2011	AM Peak	1.086752	reliable
		PM Peak	1.156643	reliable
	2012	AM Peak	1.066693	reliable
		PM Peak	1.157025	reliable
	2013	AM Peak	1.055256	reliable
		PM Peak	1.239177	reliable
	2014	AM Peak	1.078932	reliable
		PM Peak	1.439039	reliable
	2015	AM Peak	1.088883	reliable
		PM Peak	1.579197	unreliable
125-04778	2011	AM Peak	1.087115	reliable
		PM Peak	1.671404	unreliable
	2012	AM Peak	1.073568	reliable
		PM Peak	1.652765	unreliable
	2013	AM Peak	1.061116	reliable
		PM Peak	1.734116	unreliable
	2014	AM Peak	1.091238	reliable
		PM Peak	1.887138	unreliable
	2015	AM Peak	1.104677	reliable
		PM Peak	2.035405	unreliable
125N04779	2011	AM Peak	1.073752	reliable
		PM Peak	1.951631	unreliable
	2012	AM Peak	1.047247	reliable
		PM Peak	1.918434	unreliable
	2013	AM Peak	1.045836	reliable
		PM Peak	2.049454	unreliable
	2014	AM Peak	1.073958	reliable
		PM Peak	2.306239	unreliable
	2015	AM Peak	1.104735	reliable
		PM Peak	2.606662	extremely unreliable
125-04779	2011	AM Peak	1.087547	reliable
		PM Peak	1.996295	unreliable
	2012	AM Peak	1.068872	reliable
		PM Peak	1.980436	unreliable
	2013	AM Peak	1.059216	reliable
		PM Peak	2.078437	unreliable
	2014	AM Peak	1.087439	reliable
		PM Peak	2.336153	unreliable

	2015	AM Peak	1.112278	reliable
		PM Peak	2.701556	extremely unreliable
125N04780	2011	AM Peak	1.096659	reliable
		PM Peak	2.450353	unreliable
	2012	AM Peak	1.069158	reliable
		PM Peak	2.427968	unreliable
	2013	AM Peak	1.064913	reliable
		PM Peak	2.486232	unreliable
	2014	AM Peak	1.095065	reliable
		PM Peak	2.692032	extremely unreliable
	2015	AM Peak	1.121108	reliable
		PM Peak	3.188528	extremely unreliable
125-04780	2011	AM Peak	1.103459	reliable
		PM Peak	2.228185	unreliable
	2012	AM Peak	1.080457	reliable
		PM Peak	2.18364	unreliable
	2013	AM Peak	1.078116	reliable
		PM Peak	2.299837	unreliable
	2014	AM Peak	1.109081	reliable
		PM Peak	2.585503	extremely unreliable
	2015	AM Peak	1.130885	reliable
		PM Peak	3.203165	extremely unreliable
125N04781	2011	AM Peak	1.092669	reliable
		PM Peak	2.231417	unreliable
	2012	AM Peak	1.069801	reliable
		PM Peak	2.200292	unreliable
	2013	AM Peak	1.068666	reliable
		PM Peak	2.315463	unreliable
	2014	AM Peak	1.095516	reliable
		PM Peak	2.548419	extremely unreliable
	2015	AM Peak	1.128063	reliable
		PM Peak	3.239673	extremely unreliable
125-04781	2011	AM Peak	1.09313	reliable
		PM Peak	1.986998	unreliable
	2012	AM Peak	1.077524	reliable
		PM Peak	2.020843	unreliable
	2013	AM Peak	1.071323	reliable

		PM Peak	2.141087	unreliable
	2014	AM Peak	1.105254	reliable
		PM Peak	2.447723	unreliable
	2015	AM Peak	1.137644	reliable
		PM Peak	3.244007	extremely unreliable
125N04782	2011	AM Peak	1.108528	reliable
		PM Peak	2.093219	unreliable
	2012	AM Peak	1.098034	reliable
		PM Peak	2.182033	unreliable
	2013	AM Peak	1.086291	reliable
		PM Peak	2.3169	unreliable
	2014	AM Peak	1.128052	reliable
		PM Peak	2.52807	extremely unreliable
	2015	AM Peak	1.174823	reliable
		PM Peak	3.268016	extremely unreliable
125-04782	2011	AM Peak	1.139576	reliable
		PM Peak	1.946367	unreliable
	2012	AM Peak	1.149697	reliable
		PM Peak	2.006649	unreliable
	2013	AM Peak	1.140428	reliable
		PM Peak	2.217501	unreliable
	2014	AM Peak	1.200691	reliable
		PM Peak	2.466736	unreliable
	2015	AM Peak	1.311312	reliable
		PM Peak	3.219905	extremely unreliable
125N04783	2011	AM Peak	1.201061	reliable
		PM Peak	2.248207	unreliable
	2012	AM Peak	1.224649	reliable
		PM Peak	2.272389	unreliable
	2013	AM Peak	1.30275	reliable
		PM Peak	2.568087	extremely unreliable
	2014	AM Peak	1.390203	reliable
		PM Peak	2.889162	extremely unreliable
	2015	AM Peak	1.621884	unreliable
		PM Peak	3.754898	extremely unreliable
125-04783	2011	AM Peak	1.622176	unreliable

		PM Peak	3.127658	extremely unreliable
	2012	AM Peak	1.625492	unreliable
		PM Peak	3.025465	extremely unreliable
	2013	AM Peak	1.838214	unreliable
		PM Peak	3.433248	extremely unreliable
	2014	AM Peak	1.943838	unreliable
		PM Peak	3.597916	extremely unreliable
	2015	AM Peak	2.226752	unreliable
		PM Peak	4.710018	extremely unreliable
125N04784	2011	AM Peak	1.59567	unreliable
		PM Peak	3.099822	extremely unreliable
	2012	AM Peak	1.747629	unreliable
		PM Peak	3.336998	extremely unreliable
	2013	AM Peak	2.005121	unreliable
		PM Peak	4.040171	extremely unreliable
	2014	AM Peak	2.33333	unreliable
		PM Peak	4.088657	extremely unreliable
	2015	AM Peak	2.774659	extremely unreliable
		PM Peak	5.453655	extremely unreliable
125-04784	2011	AM Peak	1.369232	reliable
		PM Peak	1.552133	unreliable
	2012	AM Peak	1.562451	unreliable
		PM Peak	2.042349	unreliable
	2013	AM Peak	1.856781	unreliable
		PM Peak	2.891148	extremely unreliable
	2014	AM Peak	2.117868	unreliable
		PM Peak	2.877631	extremely unreliable
	2015	AM Peak	2.648557	extremely unreliable
		PM Peak	3.750329	extremely unreliable
125N04785	2011	AM Peak	1.379704	reliable

		PM Peak	1.710557	unreliable
	2012	AM Peak	1.600302	unreliable
		PM Peak	2.082473	unreliable
	2013	AM Peak	1.869266	unreliable
		PM Peak	2.946074	extremely unreliable
	2014	AM Peak	2.11194	unreliable
		PM Peak	2.850888	extremely unreliable
	2015	AM Peak	2.629201	extremely unreliable
		PM Peak	3.614222	extremely unreliable
125-04785	2011	AM Peak	1.285555	reliable
		PM Peak	1.439401	reliable
	2012	AM Peak	1.486278	reliable
		PM Peak	1.661656	unreliable
	2013	AM Peak	1.734608	unreliable
		PM Peak	2.132752	unreliable
	2014	AM Peak	2.004696	unreliable
		PM Peak	2.227338	unreliable
	2015	AM Peak	2.471819	unreliable
		PM Peak	2.786519	extremely unreliable
125N04786	2011	AM Peak	1.185841	reliable
		PM Peak	1.159869	reliable
	2012	AM Peak	1.335137	reliable
		PM Peak	1.207162	reliable
	2013	AM Peak	1.498675	reliable
		PM Peak	1.368404	reliable
	2014	AM Peak	1.784866	unreliable
		PM Peak	1.461201	reliable
	2015	AM Peak	2.219247	unreliable
		PM Peak	1.538909	unreliable
125-04786	2011	AM Peak	1.126621	reliable
		PM Peak	1.099779	reliable
	2012	AM Peak	1.221667	reliable
		PM Peak	1.083336	reliable
	2013	AM Peak	1.422795	reliable
		PM Peak	1.086672	reliable
	2014	AM Peak	1.663856	unreliable
		PM Peak	1.138625	reliable
	2015	AM Peak	2.131713	unreliable

		PM Peak	1.12029	reliable
125N04787	2011	AM Peak	1.130025	reliable
		PM Peak	1.093594	reliable
	2012	AM Peak	1.199717	reliable
		PM Peak	1.083943	reliable
	2013	AM Peak	1.352796	reliable
		PM Peak	1.090136	reliable
	2014	AM Peak	1.517629	unreliable
		PM Peak	1.126282	reliable
	2015	AM Peak	1.914607	unreliable
		PM Peak	1.148775	reliable
125-04787	2011	AM Peak	1.606986	unreliable
		PM Peak	1.117596	reliable
	2012	AM Peak	1.657024	unreliable
		PM Peak	1.178951	reliable
	2013	AM Peak	1.766327	unreliable
		PM Peak	1.243485	reliable
	2014	AM Peak	1.933891	unreliable
		PM Peak	1.457737	reliable
	2015	AM Peak	2.196673	unreliable
		PM Peak	1.501952	unreliable
125N04788	2011	AM Peak	1.813729	unreliable
		PM Peak	1.084947	reliable
	2012	AM Peak	1.901264	unreliable
		PM Peak	1.069443	reliable
	2013	AM Peak	2.094663	unreliable
		PM Peak	1.113443	reliable
	2014	AM Peak	2.319554	unreliable
		PM Peak	1.260783	reliable
	2015	AM Peak	2.621807	extremely unreliable
		PM Peak	1.248876	reliable
125-04788	2011	AM Peak	1.724216	unreliable
		PM Peak	1.08607	reliable
	2012	AM Peak	1.70581	unreliable
		PM Peak	1.056984	reliable
	2013	AM Peak	2.087728	unreliable
		PM Peak	1.067835	reliable
	2014	AM Peak	2.138059	unreliable
		PM Peak	1.114467	reliable
	2015	AM Peak	2.62928	extremely unreliable
		PM Peak	1.128888	reliable

125N04789	2011	AM Peak	1.414372	reliable
		PM Peak	1.132989	reliable
	2012	AM Peak	1.417439	reliable
		PM Peak	1.095596	reliable
	2013	AM Peak	1.614751	unreliable
		PM Peak	1.101156	reliable
	2014	AM Peak	1.672655	unreliable
		PM Peak	1.118785	reliable
	2015	AM Peak	1.969794	unreliable
		PM Peak	1.107573	reliable
125-04789	2011	AM Peak	1.076342	reliable
		PM Peak	1.058773	reliable
	2012	AM Peak	1.086131	reliable
		PM Peak	1.03752	reliable
	2013	AM Peak	1.191075	reliable
		PM Peak	1.044097	reliable
	2014	AM Peak	1.232064	reliable
		PM Peak	1.053826	reliable
	2015	AM Peak	1.424449	reliable
		PM Peak	1.056129	reliable
125N04790	2011	AM Peak	1.06431	reliable
		PM Peak	1.059928	reliable
	2012	AM Peak	1.046646	reliable
		PM Peak	1.040616	reliable
	2013	AM Peak	1.069777	reliable
		PM Peak	1.045092	reliable
	2014	AM Peak	1.150837	reliable
		PM Peak	1.05749	reliable
	2015	AM Peak	1.240532	reliable
		PM Peak	1.056854	reliable
125-04790	2011	AM Peak	1.048283	reliable
		PM Peak	1.053602	reliable
	2012	AM Peak	1.038412	reliable
		PM Peak	1.03661	reliable
	2013	AM Peak	1.042941	reliable
		PM Peak	1.038357	reliable
	2014	AM Peak	1.057456	reliable
		PM Peak	1.046842	reliable
	2015	AM Peak	1.065615	reliable
		PM Peak	1.048435	reliable
125N04791	2011	AM Peak	1.067182	reliable
		PM Peak	1.065286	reliable

	2012	AM Peak	1.059804	reliable
		PM Peak	1.051838	reliable
	2013	AM Peak	1.050926	reliable
		PM Peak	1.0517	reliable
	2014	AM Peak	1.072386	reliable
		PM Peak	1.062536	reliable
	2015	AM Peak	1.073094	reliable
		PM Peak	1.068278	reliable
125-04791	2011	AM Peak	1.230269	reliable
		PM Peak	1.249547	reliable
	2012	AM Peak	1.22135	reliable
		PM Peak	1.237473	reliable
	2013	AM Peak	1.229089	reliable
		PM Peak	1.280499	reliable
	2014	AM Peak	1.164035	reliable
		PM Peak	1.077647	reliable
	2015	AM Peak	1.058425	reliable
		PM Peak	1.065829	reliable