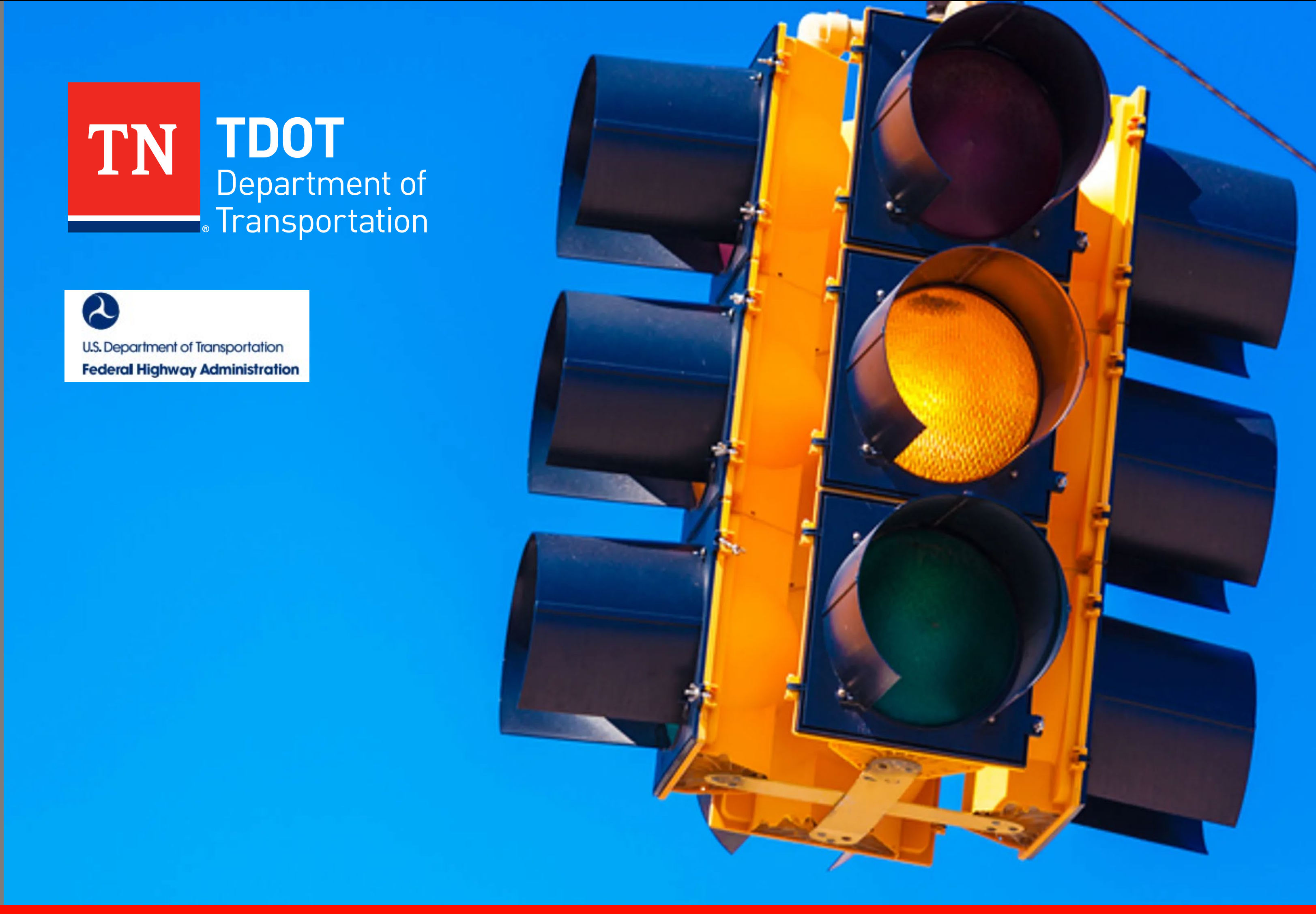

Using Big Data and Machine Learning to Evaluate and Rank the Performance of Traffic Signals in Tennessee

Research Final Report from Middle Tennessee State University | Lei Miao, Ph.D., Piro Meleby, and Christopher Winfrey | June 30, 2022

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Transportation agencies are tasked with making decisions and taking actions to fight congestion and improve road conditions using the methods and resources available to them. Performance evaluations of traffic conditions at signalized intersections and arterials provide practical data for the agencies to make well-informed decisions for targeted retiming solutions. However, there are no widely accepted standards of evaluating traffic signals, and examining each intersection manually is very costly and time consuming. As a result, many agencies simply retime the traffic signals every 3-5 years or rely on citizens' complaints to prioritize traffic signal retiming. In this work, segmented probe vehicle data from the RITIS website was used to implement a cost-effective approach that ranks the major traffic signals in Tennessee in the scale of 0 to 10. First, signalized intersections were extracted using the TMC segments. Then, three metrics were selected based on the available data from the RITIS website, and a ranking formula that incorporate these metrics as well as factors such as different time of the day and different days of the week was designed. September 2021 traffic data was used to calculate the ranking of the intersections, and an online database was developed to display, browse, and query the traffic signal ranking information. K-means, an unsupervised machine learning approach, was utilized to divide the signals into 6 clusters, using which the weighting factors of the ranking formula were finetuned. This work is the first step towards an automated evaluation system that can monitor the performance of traffic signals in real-time.</td></tr>
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The list of peer reviewed conference papers and journal articles are listed below:

- D. Leitner, P. Meleby, L. Miao, "Recent Advances in Traffic Signal Performance Evaluation", *Journal of Traffic and Transportation Engineering*, Aug 2022, https://doi.org/10.1016/j.jtte.2022.06.002
- P. Meleby, C. Winfrey, L. Miao, "Development of a Traffic Signal Performance Ranking Online Database for the State of Tennessee", ASCE International Conference on Transportation and Development", Seattle, WA, June 2022
- P. Meleby, C. Winfrey, L. Miao, "Using Big Data and Machine Learning to Rank Traffic Signals in the State Tennessee", under preparation for journal publication

Executive Summary

Travel signal retiming is one of the most basic strategies to help mitigate congestion. However, the performance of traffic signals is costly to evaluate, and agencies often rely on citizens' complaints and periodic schedules (e.g., every three years) to perform signal retiming. As a result, many traffic signals are not retimed in a timely manner when there is a change in traffic pattern. The objective of this project was to develop a low-cost database that ranks the traffic signals in Tennessee on a scale of 0 to 10. The ranking database provides performance evaluation of traffic signals and helps agencies prioritize traffic signal retiming.

In this work, segmented probe vehicle data from the Regional Integrated Transportation Information System (RITIS) website was used. First, intersections were extracted using the Travel Message Channel (TMC) segments. Three metrics were then selected based on the available data from the RITIS website, and a ranking formula that incorporates these metrics as well as factors such as different time of the day and different days of the week was designed. In September 2021, traffic data was used to calculate the ranking of the intersections, and an online database was developed to display, browse, and query the traffic signal ranking information. K-means, an unsupervised machine learning approach, was utilized to divide the signals into 6 clusters, using which the weighting factors of the ranking formula were finetuned. The ranking formula results were compared with the Level-of-Service (LOS) letter grade ranking provided by local transportation agencies, and it showed that the former results were mostly harsher. This work is the first step towards an automated evaluation system that can monitor the performance of traffic signals in real-time.

Key Findings

The key findings based on this project are concluded as follows:

- Among the 1655 Tennessee traffic signals in the database, 18.73% have excellent performance, 65.49% have good performance, and 15.78% are performing poorly.
- Discussion with traffic engineers in City of Murfreesboro and City of Franklin indicated that urban traffic signals tend to be ranked lower than rural ones.
- Local agencies do not have a systematic way to evaluate traffic signal performance. Based on interactions with City of Murfreesboro and City of Franklin, local agencies still rely on LOS letter grades and sometimes outdated traffic data to evaluate traffic signal performance. The LOS letter grades are solely determined by the average control delay, which are often hard to obtain. This observation indicates that the work done in this project could be very helpful to the local agencies.
- Machine Learning could be very useful in evaluating traffic signal performance. In this project, unsupervised learning was used to automatically group intersections into clusters. The machine learning results not only provide another way to evaluate the performance, but also help us fine tune the weighting factors in the ranking formula.

Key Recommendations

The research team makes the following recommendations to the Tennessee Department of Transportation (TDOT) based on the research findings:

- More outreach should be conducted with local transportation agencies to make them aware of the ranking database. Local agencies can provide feedback regarding the traffic signal ranking data while also benefiting from the ranking results by retiming their traffic signals in a more organized way.
- To expand the database and create opportunities for additional intersections to be ranked, TDOT should work with RITIS/INRIX to include more side roads in TMC/eXtreme Definition segments.
- Due to the high recurring cost of using Amazon webservices to host the online database, the research team recommends either TDOT or the Middle Tennessee State University host the website.
- Safety should be included in the ranking calculation. Because the access to the traffic safety related data was not given, safety was not involved in the ranking formula. However, it is recommended that safety related factors are added to the ranking formula in the future.
- Need to monitor traffic signal performance in real-time. The current signal ranking results were calculated using historical traffic data in September 2021. It would be much more useful if the real-time score can be calculated and displayed online. This would require pulling data from the RITIS website periodically and frequently or implementing an Automated Traffic Signal Performance Measures (ATSPM) system, but the benefits could be huge because the agents would be able to tell the performance of a specific signal in real-time.

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Glossary of Key Terms and Acronyms

ATSPM	Automated Traffic Signal Performance Measures
BMS	Bluetooth Monitoring Station
GPS	Global Positioning System
LOS	Level of Service
PDA	Probe Data Analytics
PTI	Planning Time Index
RITIS	Regional Integrated Transportation Information System
TMC	Traffic Message Channel
TOD	Time of Day
XDs	eXtreme Definition Segments

Chapter 1 Introduction

1.1 Problem Description

The increase in the number of vehicles on roads has led to a rise in traffic congestion, especially in highly populated areas. The national cost of congestion in the United States has increased by almost six-fold, from $24 billion in 1982 to $121 billion in 2011 [1]. At the end of that period, the commuters felt the congestion's effect in the form of an additional 5.5 billion travel hours and 2.9 billion more gallons of fuel. The upward trajectory of congestion has since continued, with 2019's pre-COVID-19 national congestion cost rising to $190 billion [2]. Whereas the impact of congestion on the commuter and the government can be observed almost immediately, its environmental impact is more drawn out and much more challenging to remedy. It is estimated that 29% of all emissions in 2019 were attributed to the transportation sector, with more than half of that contributed by light-duty vehicles including passenger cars and light-duty trucks [3]. A sum of 36 million tons of greenhouse gases produced in 2019 were created due to congestion alone [2]. Therefore, it is important to mitigate congestion on roadways to minimize the economic and environmental impact. As illustrated In Figure 1.1 below, there are multiple ways to reduce congestion. For example, it can be alleviated through limiting the number of vehicles through policy changes or road optimization efforts to ensure maximum utility of available facilities.

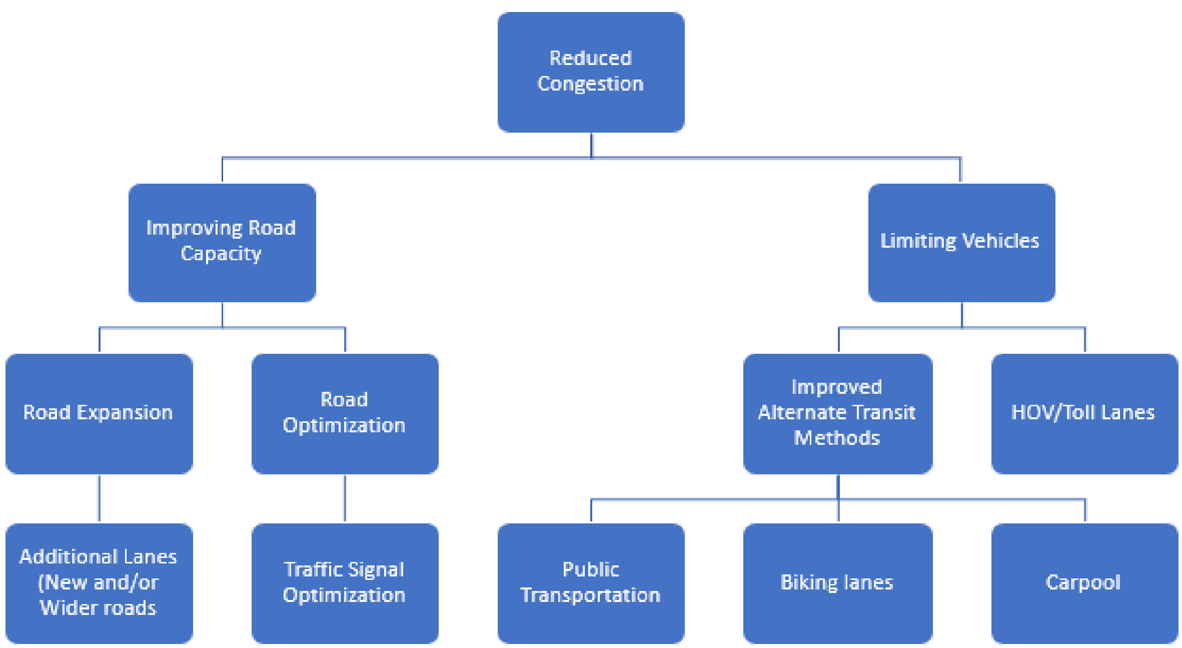

Figure 1.1 Congestion-Relief Methods.

Congestion-relief efforts made under the consideration of the former often involve investment in expansion of alternate forms of transport, including subways, light rails and trams, carpooling and expanded bicycling facilities. Since these undertakings aim to reduce the number of vehicles on the road, they are mostly considered when reducing emissions and pollution is the main goal or in areas where support for such policies is high.

The alternative approach to fighting congestion focuses on road capacity, in which roads are either expanded or optimized. Road expansion projects are often expensive endeavors for transportation agencies and cause congestion and bottlenecking along and at nearby roads and intersections due to limited lane availability and traffic detouring. Furthermore, it has been documented that this approach does not significantly improve congestion, hence not completely justifying the investment [4]. Duranton et al. conducted a study based on the “fundamental law of highway congestion” [5], in which the law was expanded beyond highways onto major roads [6]. Their findings suggested that increasing road capacity is not an appropriate approach to tackle congestion. Additional studies [7, 8] reached similar conclusions, with the latter suggesting road pricing as an alternative solution to congestion. However, congestion pricing projects like the introduction of toll lanes do not receive massive or sustained support from the public [9, 10, 11]. These methods often require significant investment from the government, policy changes and public support, a significant change in the commuting patterns of the public, additional travel cost, or combinations of these effects.

Road optimization projects are less intrusive to drivers due to the utilization of already existing infrastructure and at no significant cost to the driver, hence garnering greater support [12]. Some simple solutions include the use of alternate lanes to increase the flow of traffic in the congested direction while operations including optimization of traffic signals performance are more complex. There are more than 272,000 traffic signals in the U.S. alone, and traffic signal retiming is one of the most cost-effective ways to improve traffic flow and mitigate congestion [13]. Each state or local transportation agency in the United States has a considerable number of traffic signals under its purview, and many of these agencies do not have a framework through which signal performance is analyzed to directly impact retiming efforts [14, 15]. Instead, these agencies rely on citizens’ complaints to respond to congestion at specific intersections, and random periodic schedules of up to five years to retime traffic signals. These methods are slow for the former, and highly ineffective and irregular for the latter. In both cases, poorly performing signals are not correctly identified, and the agencies do not have said signal performance evaluation framework to observe the effects of the retiming efforts. Such a framework requires large quantities of data to capture the actual conditions on the roads. Signal performance data is time-based and includes mostly speed and travel time-related measures, as well as occupancy and utility measures. Performance evaluations are used to prioritize which traffic signals need retiming to complete a feedback loop of continuous improvement of a traffic control system, as illustrated in Figure 1.2.

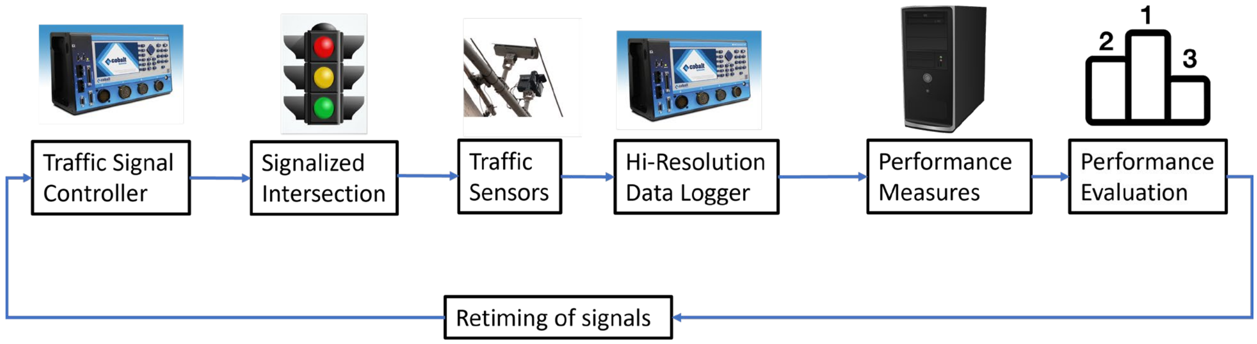

Figure 1.2 Process Flow of Traffic Signal Performance Evaluation.

1.2 Research Objective

It is imperative that transportation agencies employ a systematic approach to evaluate traffic signal performance to provide valuable insights on the flow of traffic and aid in retiming efforts. However, there is no universal approach to do this, and it would also require significant amounts of resources and associated costs. In this work, the objective was to develop a low-cost and yet effective ranking database that gives each major Tennessee traffic signal a score between 0 and 10. The ranking results are easy to understand so that agencies can evaluate the performance of traffic signals and prioritize retiming efforts.

1.3 Report Organization

The remainder of this project report is structured as follows. Chapter 2 explores some of these endeavors in which probe vehicle data was utilized to evaluate and rank traffic signals. In Chapter 3, the methodologies that build on the existing body of research to provide performance rankings for signalized intersections in Tennessee are presented; this chapter covers how signalized intersections were identified using the geographical information provided by probe vehicle data and how a rank for each intersection on a scale from 0-10 was determined. In Chapter 4, the results and their implications are discussed. Some preliminary work for Phase II of the project is presented in Chapter 5. Conclusions and an outlook for future works are included in Chapter 6.

Chapter 2 Literature Review

Remias et al. evaluated segment-based probe vehicle data performed four case studies to test the effectiveness of different methods for traffic signal performance evaluation [16]. Four data collection methods, including agency-driven probe vehicles, re-identification with pavement sensors that can detect a vehicle's magnetic fingerprint, re-identification with Metropolitan Affairs Coalition address matching using Bluetooth Monitoring Station (BMS) scanners, and crowd-sourced data (commercial probe vehicle data from INRIX). The results showed that crowd-sourced data from INRIX had the best scalability but only fair sample sizes and characterized distribution of travel times. It also highlighted the limitation of segmented probe data that is crowd-sourced to correspond to individual signalized intersections. This, coupled with the low penetration of the Traffic Message Channel (TMC) standard, which is widely used in aggregating probe vehicle data by private entities including INRIX, is a hinderance to greater use of probe vehicle data. Despite these limitations, probe vehicle data has been increasingly utilized by agencies and researchers alike to develop performance evaluation frameworks.

2.1 Signal Performance Metrics

Meijer et al. used consumer vehicle Global Positioning System (GPS) data provided by the Floating Car Database from TomTom to measure delay and turning movements at intersections in the Dutch city of Delft [17]. The authors utilized a multi-source multi-destination Dijkstra algorithm to analyze each individual measurement and link it to the most probable location on the road based on the chosen route of the vehicle. For measurement of turning movements, the results of the vehicles' GPS data were compared with a ground truth reference obtained by loop detectors and shown to be accurate with less than 3.8% error. When measuring delay, which is defined as the difference between uninterrupted and interrupted travel times through the intersection, the results from the GPS data were compared with the those from the combination of loop detectors and a time-dependent stochastic delay model. In this case, there was no ground truth reference, and the two methods provided distributions with similar trend but deviations as large as 20s during rush hour and nighttime periods. The authors proposed that the insufficient amount of GPS sample data contributed to the discrepancy.

Wünsch et al. [18] used anonymous GPS probe data from navigation devices to perform a large-scale generic analysis for the Bavarian Road Administration in Germany. The data provided was used to determine delay times and path specific travel times for road segments that contained 2,300 traffic signals. Once the data was mapped to the corresponding intersections and reference travel times were determined using free-flow speed, the key performance indexes were calculated and used to rank the intersections. The metrics analyzed were the total delay, the average delay, and the travel time index. The total delay was calculated using the total sum of the delay for vehicles at an intersection compared to free-flow speed [17], with the average delay simply being the value normalized for the number of vehicles. Lastly, the travel time index, as mentioned earlier, is the ratio of the observed travel times over the free-flow speed travel times.

Khattak et al. used travel time runs and INRIX probe vehicle data to obtain performance measures for Scalable Urban Traffic Control intersections in Pittsburgh, Pennsylvania [19]. First, GPS floating car data was collected for different time-of-day windows and travel time and speed measures were developed and evaluated for improvements. Considering the free flow travel time as the posted speed along a TMC segment, the planning time index was developed from the INRIX probe vehicle data:

$$\text{Planning Time Index (PTI)} = \frac{95^{th}\text{ Percentile travel time}}{\text{free flow travel time}}$$

Volatility and Bayesian regression models were also used to analyze performance before and after adaptive traffic control. The adaptive control was determined to have a net positive impact on speed, travel time, travel time reliability and planning time index. This study benefits from the use of multiple sources of data and different performance measures. Although it was determined that the GPS data and the probe vehicle data from INRIX showed variation, multiple other useful measures could be incorporated from probe vehicle data including congestion represented as the ratio of average speed to the free flow speed.

Cheng [20] worked with the Department of Transportation (DOT) of the City of Austin, Texas to develop and implement performance metrics to evaluate traffic signal effectiveness. Along with a modified corridor travel time, which the DOT was already using in evaluation, a few other metrics were developed: corridor travel time change, corridor throughput, side street split failures, pedestrian delay, transit speed change/transit ridership change, and reliability index change. Most data used to obtain these metrics originated from Metric Blvd. because it was the only corridor that had recently been retimed. The analysis was done on data from both before and after the retiming occurred. The travel time data did not show any significant difference between the two study periods, but this proved to be a good opportunity to compare the data sources. It was found that these data sources tended to overestimate the travel time during low levels of traffic and conversely underestimate it during peak times. Exiting throughput was monitored on W Parmer Ln. due to the presence of GRIDSMART cameras on the corridor. However, since there was no retiming done to this intersection, there were no comparisons made. To investigate side street split failures, Kimley-Horn's online dashboard and aggregate report function were used for all intersecting corridors to Metric Blvd. The before and after graphs showed a decrease in total split failures on Metric Blvd. but the side corridors did not show a significant increase. There was a lack of data for determining pedestrian delay and transit speed change, so it was undetermined if retiming had any impact on the measures. INRIX data was used to determine the reliability index and was found to show an overall increase during peak hours. Using the data available through INRIX, a list of recommended corridors to be retimed the next year were presented.

2.2 Signal Performance Rankings

The Pennsylvania DOT sponsored a study [21] to create a web dashboard interface that uses commercial probe vehicle data from INRIX to rank the performance of 138 corridors in Pennsylvania. The corridors were evaluated in terms of travel time, reliability, delay, and congestion based on segmented probe vehicle data. The data was collected from a web Application Programming Interface via windows service program and automatically stored in a Structured Query Language (SQL) database. Over the course of one year, roughly 30 billion data records were recorded. Using aggregated data across 15-minute time intervals, travel time was calculated using a normalized median speed for a given road segment. The interquartile range was used as a measurement of the reliability. Delay and congestion were measured using a plot showing a color-coded break down of a corridor based on the operating speeds for each section.

Day et al. [22] presents a methodology for analyzing and ranking arterial travel times. The analysis was performed on a series of 28 arterials with a total of 341 signalized intersections in Indiana, USA. The data consisted of individual minute by minute speed records which were then converted into travel times. To mitigate the effects from occasionally missing data, the speed records were pooled into 15-min bins, and the average of the bins was used as the measured travel time in each segment for that period. Additionally, the authors divided a typical day into three intervals: morning peak, midday, and afternoon peak. T was used to denote the length of such an interval. Since the arterials varied in length and speed limits, two normalization methods were used on the data: *(i)* calculating travel rate r_T and *(ii)* calculating the ideal-speed normalized travel time x'_T by dividing the average measured travel time by the ideal travel time. The travel rate r_T in the former method is the ratio of the average travel time over the distance of the corridor, which is basically the reciprocal of speed. In the latter method, the ideal travel time is calculated as the time it takes to traverse the corridor at the speed limit. The authors discovered that r_T and x'_T are proportional to each other. Because r_T could be arterial dependent, they considered x'_T as a better metric to rank different corridors. In addition to the ideal-speed normalized travel time, which is essentially the central tendency, the study also evaluated the normalized reliability of travel time s'_T, which is the ratio between the standard deviation of the actual travel time and the speed limit travel time. Finally, the authors came up with a ranking index for each corridor:

$$\text{index}_T = 100 \cdot \sqrt{(\max\{0, x'_T - 1\}^2 + (w \cdot s'_T)^2)},$$

where w is a weighting factor.

It was determined that the arterials with more traffic signals had higher average travel times and less reliability. This study considered a few arterials for evaluation, using only data for Wednesday which may not be representative of the typical traffic flow on the arterials for other days.

In a more recent work [23], Dunn et al. used segmented probe vehicle speed data to rank the performance of 1,026 traffic signals along 79 corridors maintained by the City of Austin, Texas for retiming purposes. The data used by this study was purchased by the City of Austin from a third-party vendor, which had a data set that covered 87% of the area in question. The data provided listed the average vehicle speed over segments of the road, with one minute speed averages. The data was downloaded from the provider and stored in a PostgreSQL database for use. The speed data was aggregated into 15-minute bins in TOD periods: morning peak (7AM-9AM), midday (11AM-1PM), and evening peak (4PM-6PM). There were three metrics used in the ranking process: the percentage of the corridor that experienced any slowdown, the percentage of the corridor that experienced a slowdown greater than 3mph, and the maximum slow-down among all the segments for any given corridor. The final ranking is based on the average of all rankings across three TODs. Finally, the authors validated their approach by comparing the corridor travel time improvement potential between two groups of arterials: the ones recommended by the ranking method and the ones selected by the City of Austin. The results indicated that the former group has 96% more travel time improvement potential than the latter group.

Segment-based probe vehicle data has also been widely used to evaluate the performance of segments on freeways. Gong and Fan [24] used a systematic approach to rank freeway segments using both intensity and reliability dimensions of traffic congestion. They discovered that two freeway segments may have very similar reliability values but significantly different intensity levels, and vice versa. Though the study focused on freeways, further research into its application to signalized intersections can provide valuable insight for traffic agencies.

Segmented probe vehicle data is a cost-friendly and readily available source of data for evaluating the performance of traffic signals, but its coarse granularity often imposes severe limitations. Specifically, some TMC segments are much longer than others and these segments may have multiple signalized intersections along their lengths. This limits the identification of intersections because there are effectively no segments at the encompassed intersections, and no representative speed and travel time data. This has been alleviated by the emergence of new types of segments such as the INRIX eXtreme Definition segments (XDs), which over more miles of road, are more flexible, and offer higher granularity than the TMC segments.

A recent work that takes advantage of the XDs data to evaluate the effectiveness of adaptive traffic signal control in Des Moines, Iowa and Omaha, Nebraska, USA is conducted by Sharma et al. [25]. Specifically, they used raw vehicle speed data to generate cumulative distribution plots of speed, travel time, and then travel rate. Using the cumulative distribution plot of travel rate and a 90% confidence interval, the authors were able to classify all the days into two categories: typical and anomalous ones. The number of anomalous days per year was used as a metric to describe the travel time reliability of a segment. For normal days, the authors used five metrics to rank each segment. The first two were directly derived from the cumulative distribution plots: (i) Median travel rate, defined as the 50th percentile of the median of each day's travel rate and (ii) Within-day variability, defined as the median of the 95th percentile and the 5th percentile of a segment's travel rate. The other three were minimum travel rate dispersion, overall travel rate variability polynomial, and overall travel rate variability linear. These three were parameter coefficients obtained through curve fitting, which was done between the 90% confidence interval and the percentiles from 0% to 100%. In the case studies, the authors further classified the segments into 8 categories based on intersection density, which is defined as the number of intersections per segment, and the Annual Average Daily Traffic per lane volume of the segment. Color-coded spider and bar plots were used to show the performance of the segments based on the five metrics for each category. Some signals were observed to be under performing and one was selected to test adaptive signal control, resulting in small positive changes.

Brenna and Venigalla also experimented on the use of XDs data by fusing high-resolution data from traffic signal systems and probe vehicle data [26]. Performance measures studied include probe vehicle speed and travel time to assess signal performance and data availability, and it was observed that minor changes in signal timing plans improve operational efficiencies of corridors. XDs are proprietary and provide better signal identification/isolation than TMC segment. The additional expense in choosing to use it over TMC segments is not feasible for many resource-strapped agencies, hence limiting its widespread application.

2.3 Summary

Probe vehicle data provides a widely available and fiscally viable option for agencies because no heavy investment is needed for purchase and installation of a wide network of sensors and traffic controllers. This makes probe vehicle data a powerful tool for in-depth analysis of traffic performance and the development of novel evaluation methods. Probe vehicle data, either from commercial companies or crowdsourcing, has become increasingly popular in the past decade, due to technological advances in smartphones, GPS, and embedded systems. However, the granularity problem of the segments makes it hard to evaluate performance at each individual intersection; as a result, most works utilizing segmented probe vehicle data focus on the performance of arterials instead. It is expected that the penetration rate will continue to rise, making probe vehicle data more useful than ever.

Most of the studies considered few performance measures to evaluate individual intersections and traffic control systems, and while they documented mostly positive results, the measures used may be insufficient to determine a true comprehensive measure of the performance at an intersection. Most of the works reviewed evaluate the performance of either individual intersections or individual corridors with multiple major intersections. The work detailed in this report seeks to provide a performance evaluation for an expansive list of intersections in the state of Tennessee. The cost-friendly and data-driven evaluation methodology proposed in this work could be used by agencies in other states as well.

Chapter 3 Methodology

In this chapter, the two different methods: the ranking formula approach and the unsupervised machine learning approach used in the research to rank traffic signals are presented. First, it is necessary to show how the data used by both methods was extracted and how the intersections were identified.

3.1 Data Source and Intersection Extraction

The data used in this project was obtained from RITIS (ritis.org), utilizing INRIX probe vehicle data accessed through the Probe Data Analytics (PDA) Suite on its website. The segment-level data encompassed most roads in Tennessee except interstate highways. The data was received as two comma-separated values (csv) files, *TMC Identification* and *Readings*: the former has the geographically identifying information for TMC segments from road names to GPS coordinates while the latter contains the probe vehicle readings obtained along the TMC segments. Figure 3.1 below summarizes the process used in the development of the intersection rankings.

Figure 3.1 A process chart showing an overview of methodology steps to obtain intersection rankings.

The TMC segments are designed such that each direction of traffic along a road has its own segment. Therefore, an ideal T-junction intersection is formed where six segments meet and a crossroad intersection is formed where eight segments meet. Segments have starting GPS coordinates at an intersection when the direction of travel is outbound and ending coordinates when the direction of travel is inbound. Using nested loops in Python 3.1, a script was written to focus on the GPS coordinates provided for each segment. Each row in the TMC Identification file was read in the primary loop, and the end latitude and end longitude column values recorded. A nested loop looked at all *other* rows and compared the end latitude and end longitude values to find an exact match. The segment codes for matches were recorded in a list that was written to a text file after each iteration. The end coordinates narrowed down the focus onto only the inbound segments for an intersection to eliminate repetition of segment impact on rankings of multiple intersections.

The PDA Suite also provides the *Trend Map* tool which proved to be of utmost importance in verifying the intersections extracted using the TMC segments. It allows users to enter specific TMC codes and maps them out. Users can also draw geometrical figures on the map and it returns all segments within its borders. To test the accuracy of the intersections extracted, random lists in the text file were copied and inserted into the Trend Map tool. Figure 3.2 shows samples of a T-junction and a crossroad intersection in the Trend Map, obtained from the initial group.

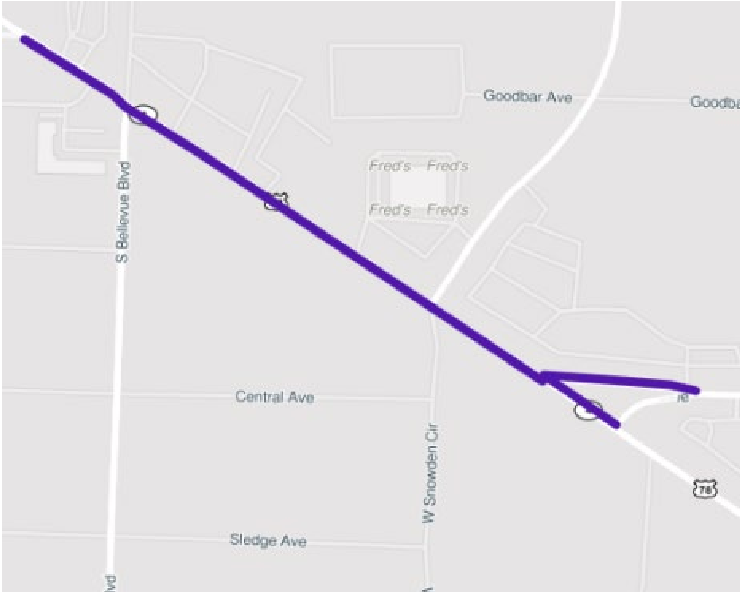

Figure 3.2 (a) A T-junction intersection at Central Ave. and TN-78, formed with three inbound TMC segments.

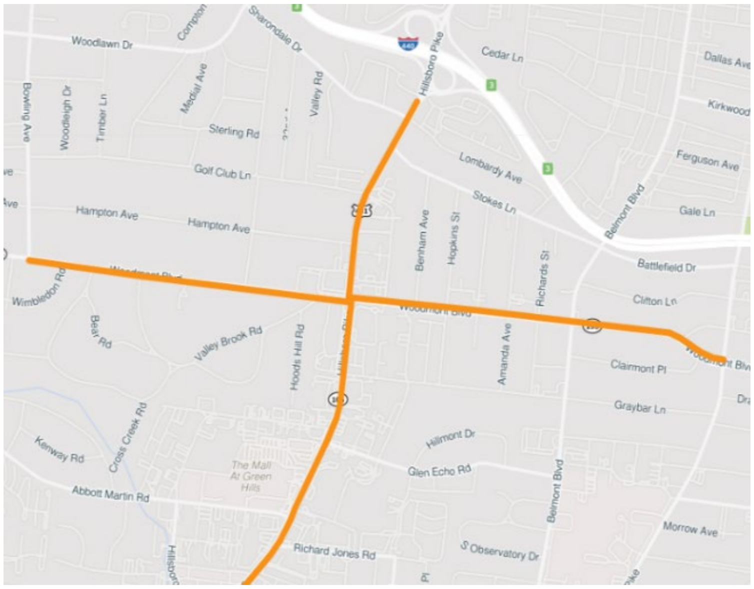

Figure 3.2 (b) A crossroad intersection at Hillsboro Pk. and Woodmont Blvd, formed with four inbound TMC segments.

Initially, only the ideal intersections as pictured (3 or 4 segments only) above were considered but their count did not reach 1000. It was imperative to further process the intersection the TMC Id file to extract more intersections. In a new Python script, the list of intersections was expanded to include *all* 'intersections' where more than one segment had the same end coordinates and were written to one text file. Each line in the file contained a group of segments with their respective road and intersection names (see Figure 3.4) pooled together in a list at the end of the line. The names for each group of segments were extracted and compared to the names for all other groups of segments to find a match. A diameter of 50m was used as a secondary filter to only match the groups in proximity. The diameter was applied to the end coordinates of the segment pairs. These hybrid intersections were appended to the original list. Figure 3.3 shows two intersections, one formed as a combination of multiple pairs of segments ending at different coordinates yet being part of the same intersection, and the other formed using only two inbound segments.

Figure 3.3 (a) A crossroad intersection at TN-104 and US-51 BYP. Four different pairs of TMC segments did not have a singular end GPS coordinate but had a match for road and intersection names.

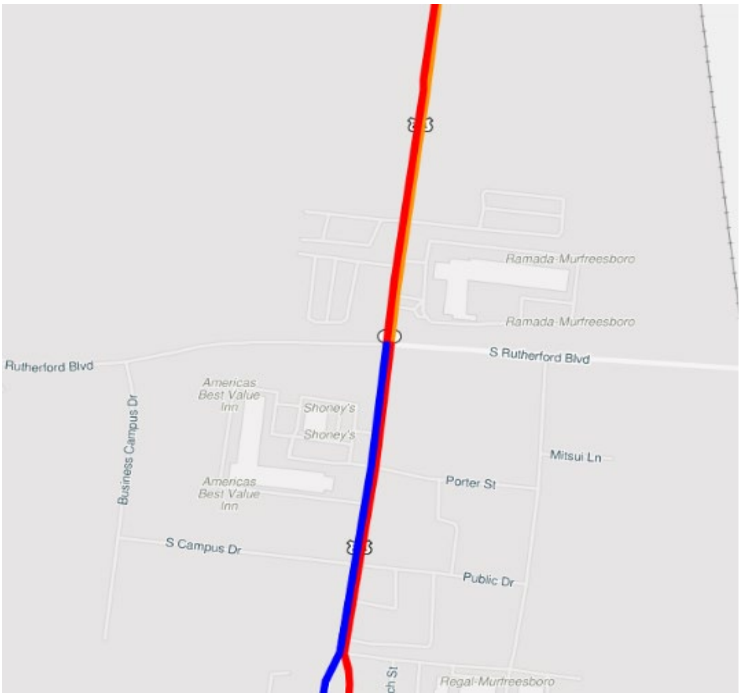

Figure 3.3 (b) The intersection of Rutherford Blvd and US-231. This intersection is formed using only two inbound segments along US-231, while Rutherford Blvd did not have any segments.

The road names include all the alternate names for the segments that have more than one value in the intersection column. An intersection constituting the segment 121N50401 in Figure 3.4, would have the names W 5TH AVE NW, US-441 and BROADWAY NW' all recorded including road names from other segments at the intersection if they were not a match for the previous three.

tmc	road	direction	intersection
121N50401	W 5TH AVE NW	WESTBOU	US-441/BROADWAY NW
121N50402	W 5TH AVE NW	WESTBOU	HALL OF FAME DR NE

Figure 3.4 A close-up of TMC segments in the TMC Identification file showing the alphanumeric TMC Id code, direction of travel along the segment, and road and intersection names.

Some intersections have stop signs, not traffic signals. Manual checking was done to remove those and ensure that there were no errors. The final number of signalized intersections is 1655.

3.2 Using a Ranking Formula

The ranking formula used three metrics to determine a rank, from 0-10, for all individual TMC segments. The rank for each intersection was then determined by averaging the ranks of the constituent TMC segments. The metrics used included congestion, Planning Time Index (PTI) and bottleneck ranking. The congestion was calculated using the average speed along the segment and hence represented the average traffic pattern along the segment, while the planning time index considered the near worst-case travel time at the 95th percentile. The bottleneck ranking shows the 1000 worst cumulative congestion locations over an extended period. The rank for each segment, R, is shown as a numerical value from 0-10, with 0 being the worst and 10 being the best.

$$R = w_p * R_p + w_c * R_c + w_b * R_b.$$

where:

- $R_p, R_c, and\ R_b$ are the contributing factors for planning time index, congestion, and bottleneck ranking, respectively. These performance metrics will be explained later in details.
- $w_p = 2.6, w_c = 5.9, and\ w_b = 1.5$ are weights assigned for planning time index, congestion, and bottleneck ranking, respectively. These weighting factors are crucial because their values affect the ranking results. The weight selection process will be explained in detail in Chapter 4.

A *Readings* file that contains probe vehicle data for the 15,007 segments in Tennessee for every day in the entire month of September 2021 was created. Speed and travel time data for the segments averaged over five minutes for three three-hour (time-of-day) windows during the day to represent the time of the day in which traffic is dense: 6AM-9AM for morning, 11AM-2PM for midday and 4PM-7PM for evening. The first two hours in each time-of-day window were considered for weekdays and the last two hours are used for weekends. In a Python script, the Readings file was processed to produce the planning time index and congestion metrics.

3.2.1 Planning Time Index

The Planning Time Index (PTI) [27] is defined as the total travel time that should be planned when an adequate buffer time is included. It compares near worst-case travel time to a travel time in light or free-flow traffic. It is calculated as the ratio of the 95th percentile value of the travel time and the free-flow travel time.

In the Python script, a loop was initialized to look at each TMC segment and find and write to a list, the indices of all the times that the segment occurs in the Readings file. This list was then used to initialize a nested loop that scanned the timestamp column to determine the date and time of day of each occurrence using the *datetime* Python library. For all the occurrences in the morning, the travel time was appended to one list for weekdays and a second list for weekends. The free-flow travel time was determined by dividing the distance of the segment, read from the TMC Identification file, by the reference (free flow) speed of the segment and the time converted to seconds. The morning planning time index for that segment during weekdays and weekends was calculated by dividing the 95th percentile value of each list by the reference speed travel time. The morning planning time index, P_1, given by

$$P_1 = \varepsilon_1 * P_{1,wd} + \varepsilon_2 * P_{1,we}$$

where:

- $P_{1,wd}$ is the planning time index for the weekday morning and $P_{1,we}$ is the planning time index for the weekend morning.
- ε_1 and ε_2 are the weekday and weekend weighting factors, respectively.

Although the study covers all days of the week, much greater weights are assigned to weekdays than weekends due to the difference in number of days in weekdays and weekends, and the sheer volume of traffic experienced by each group. After consultation with the traffic department of City of Murfreesboro, it was determined that $\varepsilon_1 = 0.9$ and $\varepsilon_2 = 0.1$.

Planning time indices for the midday period, P_2, and the evening period, P_3, were calculated similarly. The aggregate planning time index, P_m, for each segment was then computed as

$$P_m = \alpha_1 * P_1 + \alpha_2 * P_2 + \alpha_3 * P_3$$

where α_1, α_2 and α_3 are the weighting factors for the three two-hour windows in the day. Similar to how ε_1 and ε_2 are chosen, greater weights are assigned to the morning and evening time-of-day windows than midday because the traffic volume is higher during rush hours: $\alpha_1 = 0.4$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.4$.

A histogram of the values for P_m for all the TMC segments is plotted, as shown in Figure 3.5.

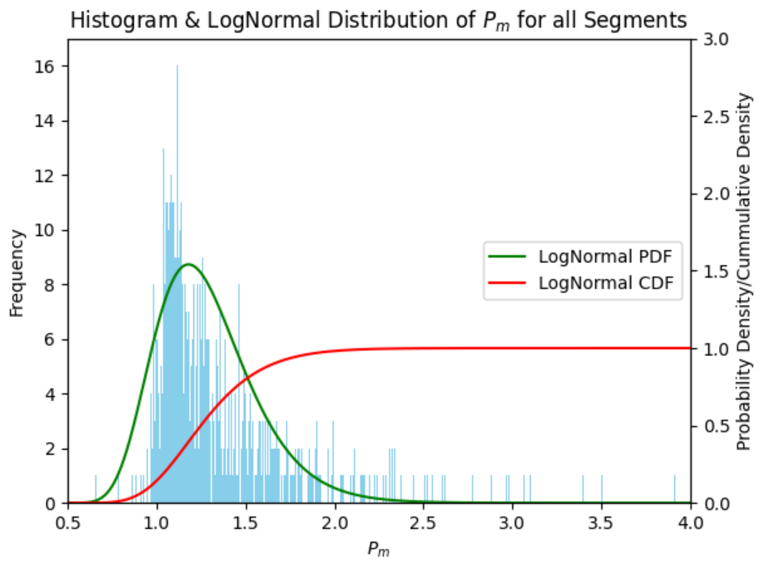

Figure 3.5 A graph showing the histogram of P_m, the approximated Lognormal probability distribution curve, and the cumulative distribution curve.

From the histogram, the distribution of the PTI is approximated to a Lognormal distribution function. The value of R_p for a TMC segment is calculated using the cumulative distribution function $F_p(x)$ for a lognormal distribution.

$$R_p(P_m) = \left(1 - \left(\int_{-\infty}^{P_m} \frac{e^{-\frac{P_m{}^2}{2}}}{\sqrt{2\pi}}\right) * \left(\frac{\ln(P_m)}{\sigma_p}\right)\right)$$

where σ_p is the standard deviation of the distribution of the log of all values of P_m.

3.2.2 Congestion

Congestion [27] is a ratio of the measured speed to the free-flow speed, and it is closely related to travel time index, the ratio of average travel time to free-flow travel time. Free flow speed is defined as the calculated "free flow" mean speed for the roadway segment in miles per hour. This attribute, formerly calculated as the 85^{th} percentile prior to March 2020, has since then been calculated as the 66th-percentile point of the observed speeds on that segment for all time periods. This establishes a reliable proxy for the speed of traffic at free flow for that segment.

The congestion was calculated in the same Python script loops as the planning time index, with a slight variation. The average speed values for each day were recorded in three separate lists for the morning, midday, and evening time-of-day windows. Averages were determined for each list and divided by the free flow speed to give congestion values C_1, C_2 and C_3, for the time windows, respectively. The aggregate daily congestion value, C_d, for one segment was calculated as

$$C_d = \alpha_1 * C_1 + \alpha_2 * C_2 + \alpha_3 * C_3$$

where $C_1, C_2, and\ C_3$ are average congestion values for the three two-hour time windows.

The C_d values for each day were then stored in two lists, one for weekdays and the other for weekends. The averages for each list, C_{wd} and C_{we} respectively were calculated and the overall congestion for the TMC segment, C_m, is shown below, and a histogram of C_m values is plotted as in Figure 3.6.

$$C_m = \varepsilon_1 * C_{wd} + \varepsilon_2 * C_{we}$$

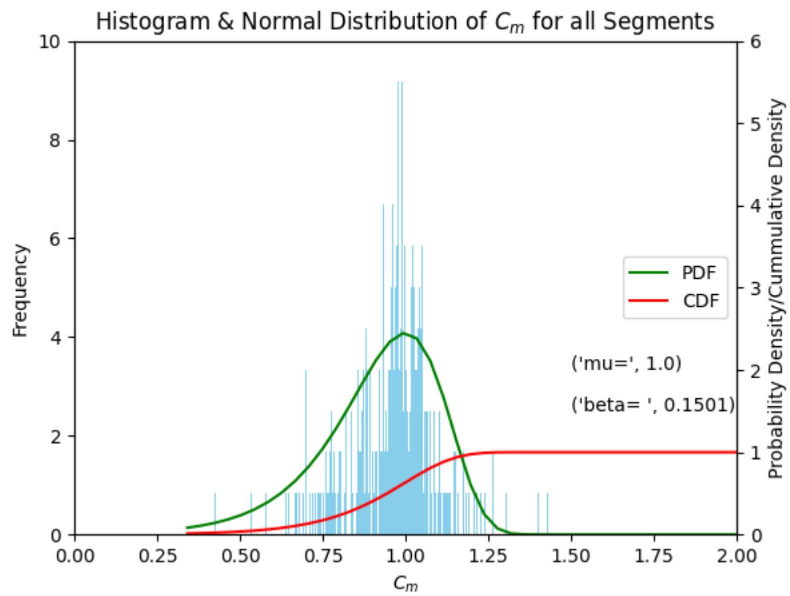

Figure 3.6 A graph showing the histogram of C_m, the approximated Gumbel probability distribution curve, and the cumulative distribution curve.

A histogram for all values of C_m for all segments was similarly plotted, and the distribution approximated to a Gumbel distribution. A probability distribution curve and a cumulative distribution curve were superimposed on the histogram and the congestion contribution, R_c, is calculated using the cumulative distribution function $F_c(x)$:

$$R_c(C_m) = 1 - e^{-e^{-(C_m-1)/0.1501}}$$

3.2.3 Bottleneck Ranking

The bottleneck ranking is a probe data analytics tool that ranks congestion along TMC segments over an extended period. The ranking was obtained as a file separate from the Readings file and it contained only the worst 1000 segments in Tennessee. The severity of bottlenecking increased as the numerical positions decreased to zero. The primary loop initialized in the planning time index section above also opened, read, and wrote the bottleneck ranking file columns into lists, and the column headers removed. Each loop iteration scanned the bottlenecking list containing the segment codes to find a match. When the segment was found, its index was incremented by 1 to indicate its position, n_b. Otherwise, n_b is zeroed. The bottleneck contribution of a TMC segment, R_b, is given by

$$R_b = \frac{n_b}{1000}$$

All TMC segments with a zero value for n_b *and* the segment ranked 1000 in the bottleneck ranking file receive R_b value of 1.

3.3 Using Unsupervised Machine Learning

In this phase of the project, unsupervised machine learning was used to evaluate the performance of traffic signals. Unsupervised machine learning means that three features: congestion, planning time index, and bottleneck ranking were provided to the system, but calculated ranking information was purposefully omitted, forcing the system to determine patterns or relationships between features.

The k-means clustering algorithm, a simple but effective unsupervised machine learning approach, was used to analyze the data set that encompasses 1,655 intersections in Tennessee and group traffic signals automatically based on the three features. The number of groups is dependent on some provided k-value. For the purposes of this research, to mimic the Level-of-Service (LOS) letter grades A-F [28], six clusters were used. The k-means clustering algorithm made available by the Scikit-Learn library, allowed us to test individual points to determine the six best centroids. These are the points within which the most points are located with minimal distance. Clusters are generated based on an individual point's proximity to one of the centroids. K-means is considered a linear clustering algorithm because clusters of points are divided by linear hyperplanes through this methodology. The performance of the k-means clustering algorithm can be visualized by examining the groupings generated on a three-dimensional plot. Note that the constrained variation of the k-means algorithm was used because of the strong imbalances in cluster size. Essentially, it allows user to set minimum and maximum cluster sizes.

The k-means clustering result serves two purposes. First, it provides an alternative way to evaluate traffic signals: it does not show a ranking between 0 and 10 for each signal, but it tells us which intersections are similar in terms of performance. Second, as discussed in Chapter 4, the k-means clustering results were also used to finetune the weighting factors used in the ranking formula above.

3.4 Development of Database and Webserver

An online database that can be easily accessed from the internet via web browsers was built. In what follows, the details of database development and webserver construction will be discussed.

3.4.1 Database

Amazon Web Services Elastic Cloud 2 (EC2) instances provide invaluable testing and development environments for remote computing with variable processing capacity, and web server hosting. One such instance was used in this study to develop a web database through which the intersection ranking results can be accessed online. In the instance, a MySQL database was created to host a table with the identifying information of all the intersections extracted, as well as the ranking information. The table consolidated data from the TMC Identification file and the calculated rankings, into columns that were classified as three categories:

- Front-end identifiers including road names, county, segment end latitude and longitude coordinates, and zip code.
- Back-end identifiers including id column set as the primary key, segment codes.

- Ranking information including overall ranking, average aggregate congestion, and average planning time index.

A python script was used to write the intersection ranking information to the database table using the MySQL Connector library. The end latitude and longitude coordinate columns were fused into one column, *GPS coordinates*. This facilitated the geolocation of the intersections using Google Maps links for each intersection. To make the database table visible via a web browser, the web development application Xampp was used.

3.4.2 Website

Xampp is embedded with a *MySQL* server and an Apache server. Both embedded servers are independent of the local Apache 2 and MySQL servers that may be running in the host machine. Both sets of servers cannot be operational at the same time, so the local servers were turned off and the *Xampp* servers booted up. In a web browser in the host machine, a localhost connection was made accessible. The MySQL server was accessed through the *PhpMyAdmin* page on the localhost, and the database table created and populated as detailed in the subsection above. A php file was written and it read the database table and displayed its contents in a web browser. The file also read and converted the GPS coordinates column into Google Maps links such that each intersection can be shown by the coordinates at its center. More php code scripts were written for the search and sort functionalities of the list of intersections, using a mix of JavaScript and Ajax programming. The search prompt is active for all columns of the table, while the sort prompt rearranges the entire table using ascending or descending order based on one column. The website was accessible at http://tntrafficsignals.org and was used by City of Murfreesboro and City of Franklin to assess the performance of their traffic signals. Per the request of TDOT and due to the high cost of hosting the website on Amazon EC2, the website has been taken down. However, an Excel spreadsheet has been attached to this report, showing all the traffic signals in the database and their rankings.

Chapter 4 Results and Discussion

4.1 Rankings Formula Results

Figure 4.1 shows the histogram of the traffic signal rankings, which is close to a normal distribution. The extreme left indicates that the poorly performing intersections had poor performance for each individual metric: an average congestion *significantly* below 1, an average planning time index *significantly* greater than 1, and a bottleneck ranking near the top of the list. These intersections were indicative of areas of near-constant heavy traffic including areas of business in downtown Nashville, Memphis, and Knoxville, and areas of periodic heavy traffic in the morning and evening time-of-day windows including areas surrounding educational establishments, K-12 and colleges/universities alike. On the other hand, the intersections at the other end of the spectrum were mostly located in rural areas. The center of the histogram is a result of different combinations of $R_p, R_c, and\ R_b$. Among the 1655 Tennessee traffic signals in the database, 18.73% have excellent performance, 65.49% have good performance, and 15.78% are performing poorly.

In the development of the metrics, each TMC segment's performance for the study period was measured up against its own best period (free flow speed and travel time). These measures, expressed as the ratios $R_p\ and\ R_c$, allowed the ranking formula to be uniformly applied across all segments without considering length of individual segment. In Figure 4.2, the vertical blue line is at average congestion value 1: all intersections occurring along this line have TMC segments on which the average speed was equal to the free flow speed. Conversely, the red horizontal line is at planning time index value 1: all intersections on this line have segments on which a driver would not need to allocate any additional time for a worst-case travel time. In Figure 4.2, an inverse correlation relationship is observed: the maximum planning time index decreases as the average congestion increases.

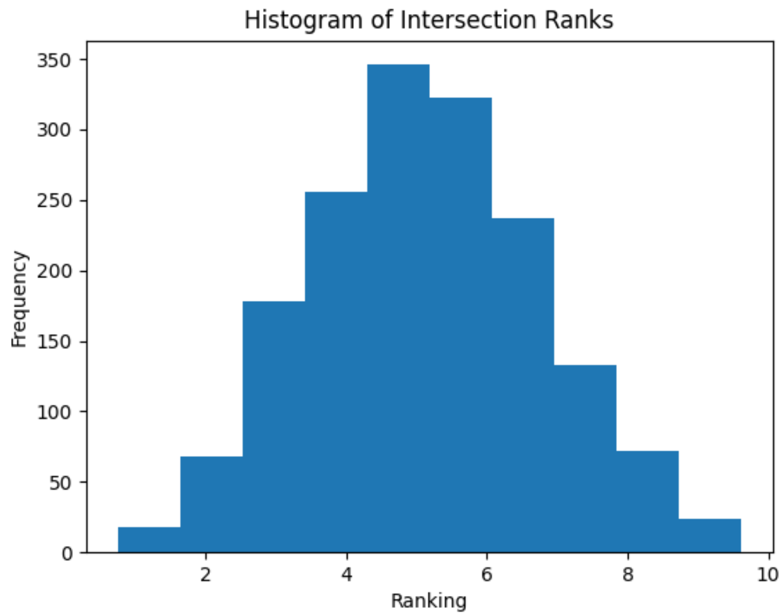

Figure 4.1 A histogram of the intersection ranks.

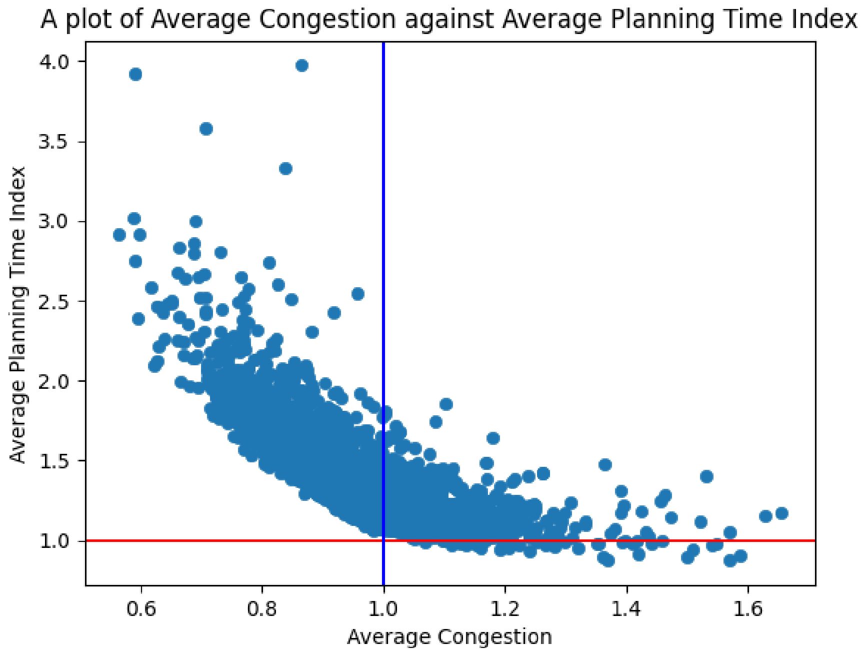

Figure 4.2 A scatter plot of congestion, C_m, against the planning time index, P_m.

4.2 Unsupervised K-Means Clustering Results

The "R" values of the three main features contributing to rank: congestion, planning time index, and bottleneck ranking were used to perform K-means constrained clustering. Figures 4.3 and 4.4 show the 6 traffic signal clusters. The green cluster is the best with the highest R values across the board, and the light blue cluster is the worst with the lowest R values. The clusters in between, ordered from the best to the worst, are: dark blue, dark brown, orange, and cyan.

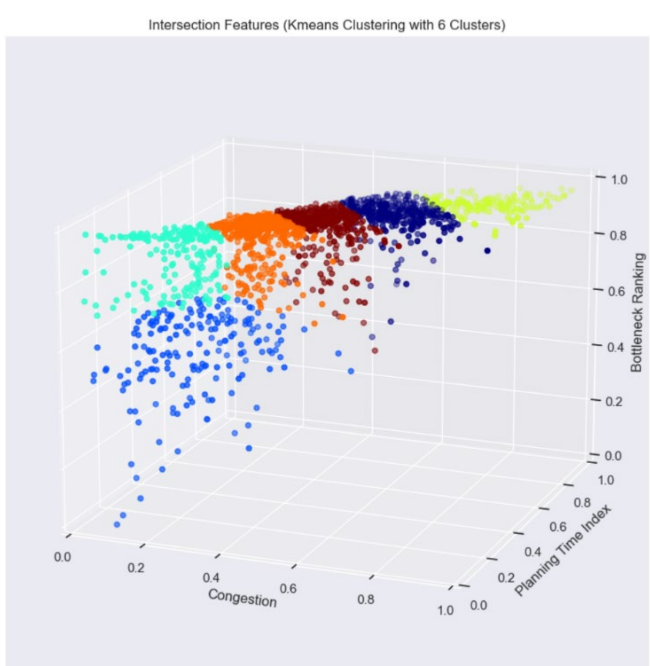

Figure 4.3 A 3-D view of the constrained K-means clustering result

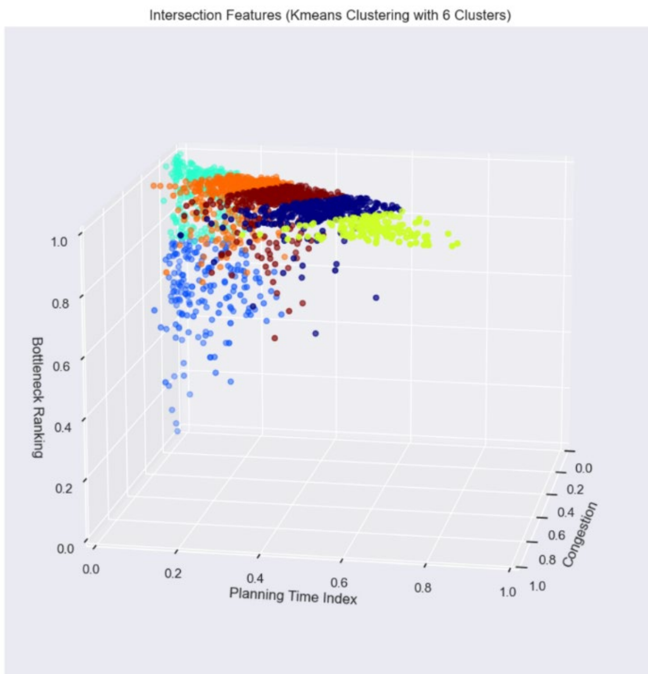

Figure 4.4 An alternate 3-D view of the constrained K-means clustering result

4.3 Weighing Factor Selection for the Ranking Formula

Recall that there are three performance measures in the ranking formula: PTI, congestion, and bottle-neck ranking. In Chapter 3, it was mentioned that the weighting factors are crucial and their final values for the three metrics are 2.6, 5.9, and 1.5, respectively, but the discussion of how exactly they were selected was deferred to Chapter 4. Next, the weighting factor selection process will be discussed in detail.

The initial weighting factors selection were 4, 4, and 2 for PTI, congestion, and bottle-neck ranking, respectively. The ranking results looked okay, but a systematic way was needed to make sure that they reflect the true performance of traffic signals. Discussions with the traffic engineers at City of Murfreesboro and City of Franklin took place, and they also provided the LOS letter grades of the traffic signals in their cities. Because some of their data was dated and the control delay was the only factor used to determine the LOS letter grades, their results were not used as a baseline to determine the weighting factors. Nonetheless, it was learned that too much weight had been given to PTI, since it is only a performance metric for the worst-case scenario. Another effort was to collect rankings of traffic signals from the public. A Google form was created, and the QR code of the link was advertised on the Middle Tennessee State University (MTSU) campus and various social medias. Dozens of responses were received. Although the input from the public was helpful in certain extent, it also had issues: *(i)* some intersections rated by the public do not exist in the database and *(ii)* the public's views vary significantly.

The final weighting factors were selected based on the unsupervised k-means clustering results. As mentioned before, the output of the k-means algorithm has 6 clusters. These clusters were manually ordered based on the performance of the signals so that cluster 1 is the best, cluster 2 is the second best, and so on. The ranking formula result 0-10 was divided evenly into 6 groups, referred to as Ranks A-F. Rank A is the best group, rank B is the second best, and so on. Essentially, the weighting factors that minimize the average distance between the ranking formula result and the k-means clustering result were selected.

Table 1 Comparison of the presence of letter grade rankings within specific clusters for k-means clustering with a resolution of 0.1.

	Rank A	Rank B	Rank C	Rank D	Rank E	Rank F	Cluster Totals
Cluster #1	56	94	0	0	0	0	150
Cluster #2	0	149	181	0	0	0	330
Cluster #3	0	0	355	43	0	0	398
Cluster #4	0	1	22	374	0	0	397
Cluster #5	0	0	0	86	108	4	198
Cluster #6	0	0	2	54	111	16	183
Rank Totals	56	243	560	557	219	20	1655

Average Distance Calculation	
Row Distance Total	94
Row Distance Total	181
Row Distance Total	43
Row Distance Total	22
Row Distance Total	90
Row Distance Total	225
Average Distance	0.3958

To better understand the average distance, see Table 1. The row distance is the sum of non-zero cell in each row multiplied with the distance from that cell to the diagonal cell in that row. For example, in the first row of Table 4.1, the row distance is $56 \times 0 + 94 \times 1 = 94$; in the sixth row, the row distance is $2 \times 3 + 54 * 2 + 111 * 1 + 16 * 0 = 225$. The average distance 0.3958 is calculated by first summing all the row distances and then divide it by the total number of traffic signals 1655. The shorter the average distance, the closer the k-means and ranking formula results are. The optimal weights that provide the minimal average distance were searched using a brute-force approach, in which possible weight combinations were tested at various levels of resolution. These resolutions are essentially the step sizes of the weighting factor changes, and their corresponding optimal weight and average distance results are provided in Table 2. Note that resolution of 0.1 was used to determine the weighting factors.

Table 2 Optimization weight and distance results based on resolution

Resolution	Weight Factors			Average Distance
	Congestion	*Planning Time Index*	*Bottleneck Ranking*	
1.0	4.0	4.0	2.0	0.4012
0.5	6.0	2.5	1.5	0.4006
0.1	5.9	2.6	1.5	0.3958

4.4 Comparison with LOS Results

The ranking formula results were compared with the LOS results provided by City of Murfreesboro and City of Franklin for a list of 54 selected signalized intersections in their cities. Figure 4.5 below shows the comparison result where [0,10] was evenly divided into 6 intervals, corresponding to the 6 LOS letter grades. Among 15 traffic signals, there is a match between the ranking formula results and the LOS grades; the ranking formula results are better at 4 intersections; for the rest of the 35 traffic signals, the ranking formula results are harsher. The difference was likely caused by the following three reasons: *(i)* the LOS grades of these intersections were solely determined by a single performance metric: the average control delay; *(ii)* the cities' data at some intersections was dated; and *(iii)* the cities might not have collected the average control delay data from different times of the day and different days of the week from an entire month.

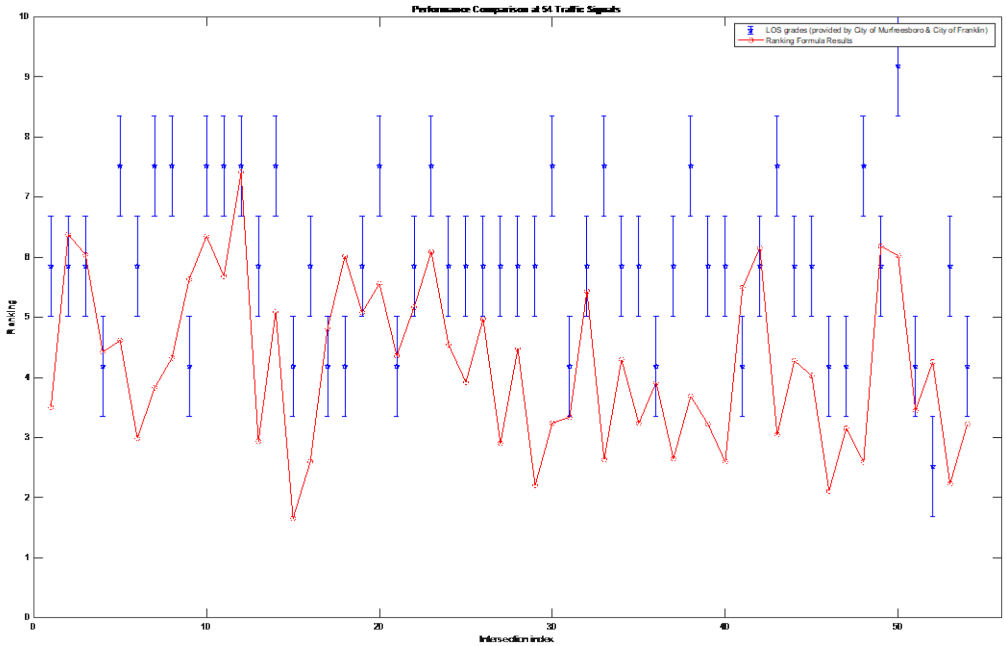

Figure 4.5 A comparison of our ranking results and the LOS letter grades at some local intersections

Chapter 5 Traffic Signal Controller Interfacing

In Phase II of the project, the general goal is to implement Automated Traffic Signal Performance Measures (ATSPM) and perform adaptive traffic signal control. In Phase I, preliminary work has been done on traffic signal controller interfacing. Specifically, an Econolite Cobalt traffic signal controller with built-in high-resolution logger was acquired to test data generation and networking capabilities in order to perform ATSPM functionalities. See Figure 5.1 for the test setup.

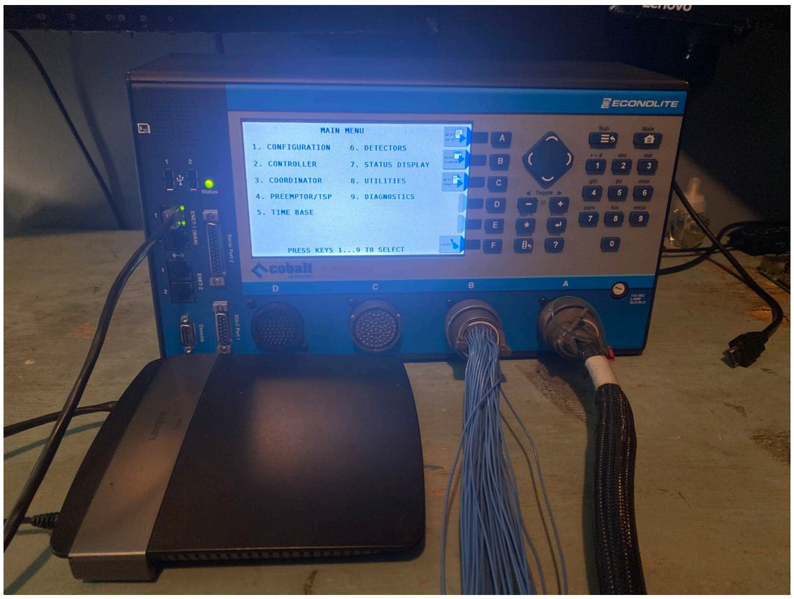

Figure 5.1 The test setup of the Econolite Cobalt Traffic Signal Controller

The tests carried out were as follows:

I. Data Generation

Loop detector calls on Phase #4 were emulated by using a switch to break the connection between the phase-specific input pins in the B-port and the ground pin in the A-port. As indicated in Figure 5.2, detectors events were observed in the log file where event type 81 and 82 represent detector OFF and detector ON events, respectively.

1	Timestamp	Event Type	Parameter								
2	50:00.0		Version #	3							
3	50:00.0		ECON_10.70.10.51_2022_07_19_1150.dat								
4	50:00.0		Intersection #	10.70.10.51							
5	50:00.0		IP Address:	10.70.10.51							
6	50:00.0		MAC Address:	00:04:81:06:4f:b1							
7	50:00.0		Controller Data Log Beginning:	50:00.0							
8	50:00.0		Phases in use:	1	2	3	4	5	6	7	8
9	50:00.1	81	4								
10	50:01.5	82	4								
11	50:01.8	81	4								
12	50:03.0	23	2								
13	50:03.0	23	6								
14	50:03.2	82	4								
15	50:03.6	81	4								
16	50:04.9	82	4								
17	50:05.3	81	4								
18	50:06.4	82	4								
19	50:06.8	81	4								
20	50:07.9	82	4								

Figure 5.2 Decoding of Log File for Data Generation testing

II. Networking

The networking capability was tested using a wireless router and a PC. The signal controller was connected to the router via an Ethernet cable, and the PC was connected to the router's Wi-Fi network. In the controller's Ethernet settings, the IP address was configured to match the subnet of the router so that all devices are on the same network. Using a Windows PC's command window, the IP address of the controller was pinged with a low round-trip response time, showing that the network connection was solid (see Figure 5.3).

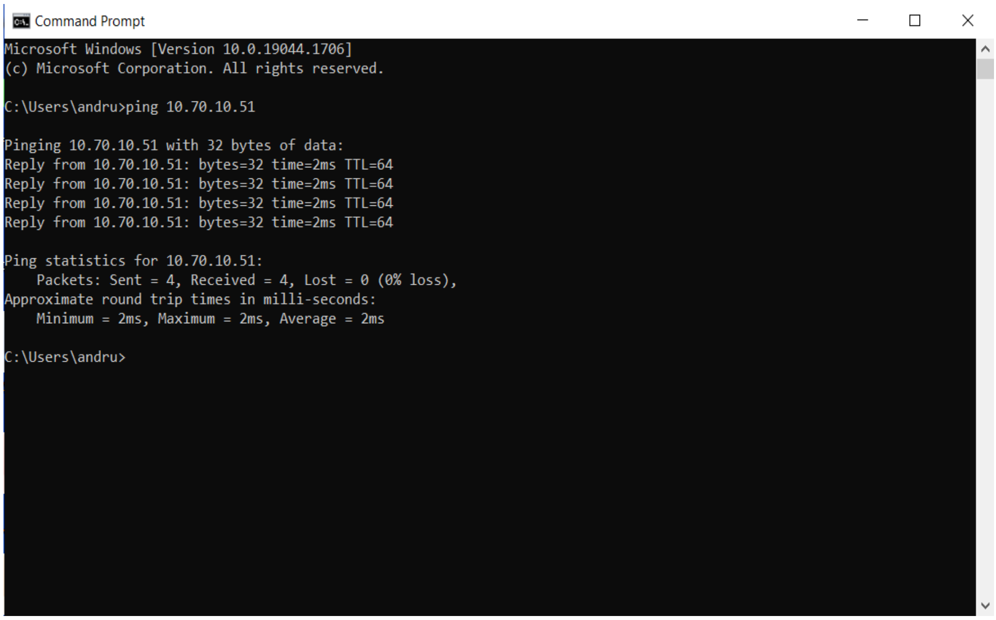

Figure 5.3 A snapshot of the Windows command prompt showing an average of 2ms ping response time

III. Web Interface

The controller was also accessed through the web front panel, using the configured IP address and port 8081. From the web interface, changes can be made to controller configurations and signal timings (see Figure 5.4 for the web front panel).

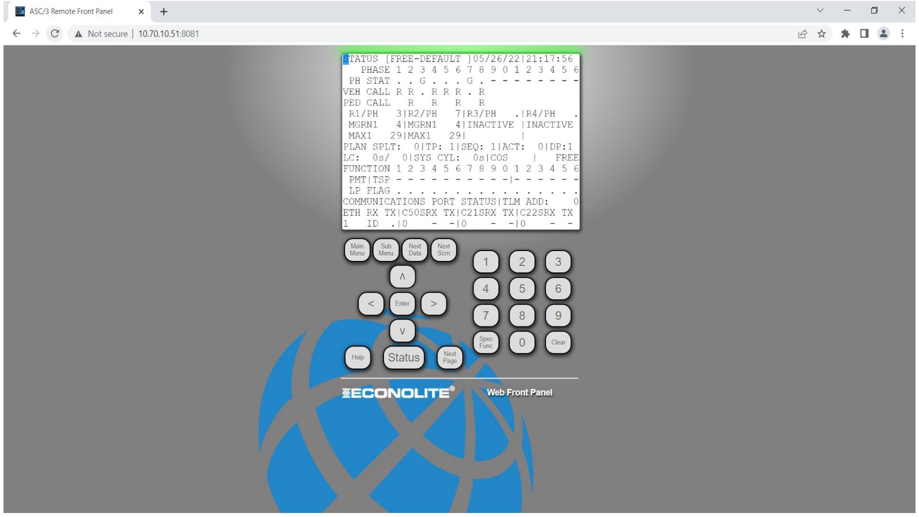

Figure 5.4 A snapshot of the Web Front Panel showing the controller status

IV. Data Logging and File Transfer

To configure the controller for ATSPM, hi-resolution data logging must be enabled in the settings. The log files that contain events at the intersection can be stored at 1-minute, 15-minute, or 1-hour intervals. Figure 5.5 shows the Web Front Panel with the interval set at 15 minutes (right middle), which is most commonly used with ATSPM applications. The log files are located on the controller, in its *set1* directory as shown in Figure 5.6 below where the *WinSCP* SSH File Transfer Protocol software on a PC was used to connect to the controller. When an ATSPM server is set up, the log files will be automatically transferred to the server for performance metrics calculation purposes.

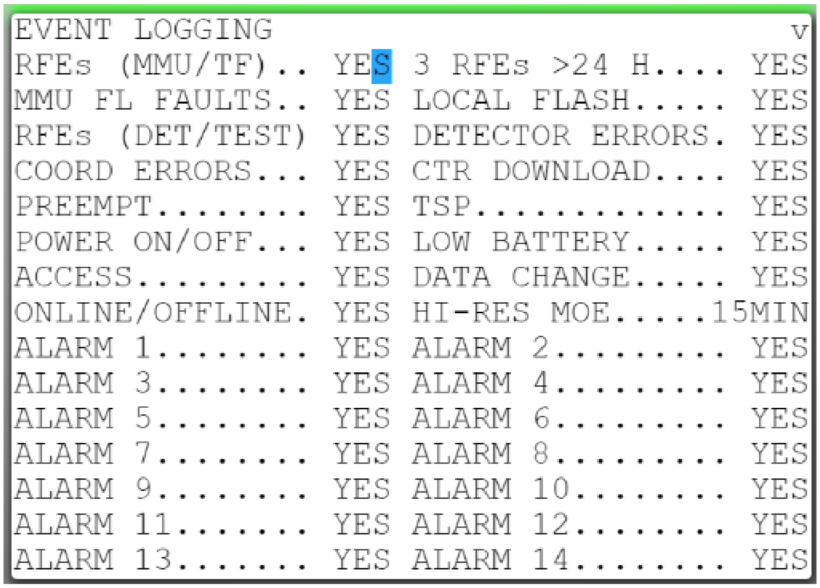

Figure 5.5 A snapshot of the Web Front Panel showing the hi-resolution event data logging enabled on the controller

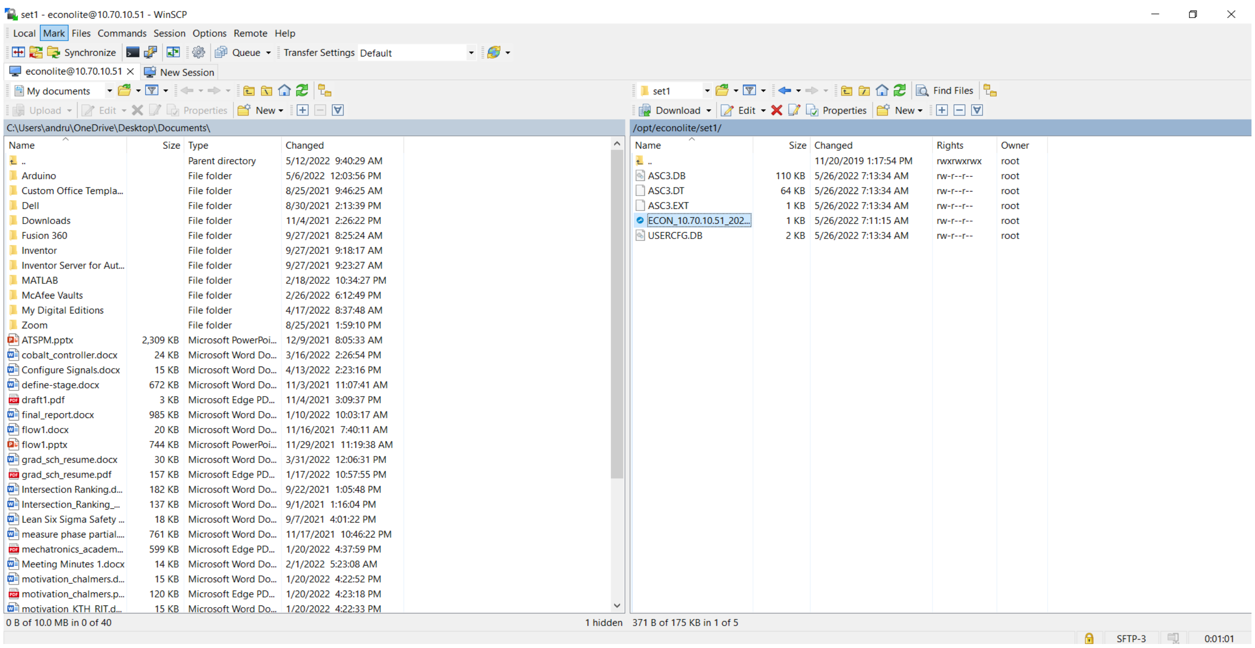

Figure 5.6 A snapshot of the WinSCP window showing the log files

Chapter 6 Conclusions

In this project, an online performance ranking database with 1655 traffic signals in Tennessee was implemented. The traffic signals were extracted using the TMC segments. Using the traffic data in September 2021 and three performance metrics: congestion, planning time index, and bottleneck ranking, a ranking formula that ranks each intersection on a scale of 0 to 10 was developed. Among the 1655 Tennessee traffic signals in the database, 18.73% have excellent performance, 65.49% have good performance, and 15.78% are performing poorly. In general, rural intersections perform better than the urban ones.

Unsupervised learning, i.e., k-means clustering was also used to divide the intersections into six clusters based on their performance. The weighting factors used in the ranking formula were finetuned using the k-means clustering results so that the average distance between the outcomes of the two different approaches was minimized. The ranking formula results were compared with the LOS letter grades of 55 intersections in the Cities of Murfreesboro and Franklin. It turned out that the ranking formula results were mostly harsher than the LOS letter grades, which only relied on the average control delay metric and were sometimes calculated using not up to date data.

The online database implemented in this project could help agencies in Tennessee prioritize signal retiming. It could also help evaluate the performance of retiming and/or adaptive traffic signal control. Possible future works involve the following aspects:

(1) Coordinating local agencies to review the performance of the worst performing 15.78% traffic signals and take actions if necessary.

(2) Including more traffic signals in the database. The TMC segments are not available for all roads, and the starting and ending points of a TMC segment are often arbitrary. Because of this, longer than usual amount of time was spent to extract traffic signals in this project. It was noticed that the TMC segments used to extract intersections are often not available on side roads, and this limited the number of intersections in the database. To expand the database to more traffic signals, TDOT would need to work with INRIX to include more side roads in the TMC segments. Another possibility is to use the XD segments provided by INRIX.

(3) Cost reduction. Hosting the online signal ranking database is somewhat costly. The monthly cost of using a powerful Amazon EC2 instance is typically between $150 and $200. Having the online database hosted at TDOT or MTSU campus would be more economical.

(4) Incorporating more metrics including safety factors. INRIX just made some additional metrics available for certain signalized intersections. If possible, these metrics should be included in the ranking formula. Safety should also be included in the ranking calculation.

(5) Need to monitor traffic signal performance in real-time. The current signal ranking results are calculated using historical traffic data in September 2021. It would be much more useful if the real-time score can be calculated and displayed online. This would require pulling data from the RITIS website periodically and frequently or implementing an ATSPM system, but the benefits could be huge because the agents would be able to tell the performance of a specific signal in real-time.

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