Decision-Making Tool for Applying Adaptive Traffic Control Systems

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Prepared for:

New York State Energy Research and Development Authority

Albany, NY

Joseph D. Tario
Senior Project Manager

and

New York State Department of Transportation

Albany, NY

Guillermo Ramos
Project Manager

Prepared by:

Rensselaer Polytechnic Institute
Department of Civil and Environmental Engineering

Troy, NY

Xuegang (Jeff) Ban, Principal Investigator
Jeffrey Wojotowicz, Senior Research Engineer
Wan Li, Graduate Student Researcher

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Abstract

Adaptive traffic signal control technologies have been increasingly deployed in real world situations. The objective of this project was to develop a decision-making tool to guide traffic engineers and decision-makers who must decide whether or not adaptive control is better suited for a given traffic corridor and/or intersections than the existing actuator control system. The decision-making tool contains a qualitative analysis method and a quantitative analysis method. The qualitative method is a decision tree that lists the critical factors that influence the decision. Traffic analysis on network performance and infrastructure analysis on the required resources could help make decisions step-by-step. The quantitative analysis method is based on big data analysis methods using a large amount of data from various sources such as detectors, 511 systems, weather, and special events. Regression models and support vector machines (SVM) were applied to distinguish "good" and "bad" signal performances, as well as adaptive and actuated control strategies. Results show satisfactory performances of the SVM methods, and a decision-making procedure was developed to guide the deployment of adaptive traffic control.

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Table of Contents

List of Figures

List of Tables

1 Introduction

Traffic signal control systems require sophisticated control and coordination schemes to achieve traffic operation objectives, such as smooth and safe traffic movements and minimum delay, among others. A variety of traffic signal control systems have been developed and installed to deliver favorable signal timings to motorists, noticeably, actuated and adaptive traffic control systems. Actuated traffic signals maintain a green signal on the busiest street until a pedestrian or a vehicle on the less traveled side street approaches the intersection. Adaptive control technologies continuously adjust the length of green time based on traffic conditions, demand, and system capacity to accommodate current traffic patterns to promote smooth flow and reduce traffic congestion.

Although actuated control systems are widely installed in the country, adaptive control systems have not been widely deployed due to the cost and uncertain outcomes. The objective of this project is to develop methods and procedures (i.e., a decision making tool) to help traffic engineers and decision-makers decide whether or not adaptive control is better suited for a given traffic corridor and/or intersection than actuated control. The decision-making tool consists of two types of methods: a qualitative analysis method based on nation-wide best practices and a quantitative analysis method using detailed traffic related data.

Existing methods for such decision-making are mainly based on before and after comparisons, using statistical or simple data analysis methods. Various studies have focused on the empirical and statistical impacts of adaptive control on traffic performance. Brilon and Wietholt (2012) conducted an empirical studies based on probe car analysis to evaluate the performance of adaptive control in Muenster, Germany. Before and after analyses compared the performance of the old system, a rule-based traffic actuation and an adaptive system. The performance index (PI) was estimated at 30% improvement by the use of adaptive system. Transit also benefited from signal priority so that travel time could be reduced by more than 20%.

Slavin et al. (2012) studied the joint impact of Sydney Coordinated Adaptive Traffic System (SCATS) and transit signal priority (TSP) on transit performance on congested corridors. The before and after analysis was conducted based on traffic and transit data along a congested urban arterial. It was determined that SCATS did not negatively affect transit performance based on statistical tests and regression analysis. They concluded that the improvement of travel time varied at different times of day and in different travel directions. Rodrigues (2014) investigated the impact of the SCATS on roadway emissions of air pollutants and travel times on a corridor in Portland, OR. Reducing the maximum cycle length by 20 seconds for a two-week trial period was proposed for the SCATS to address the problem of pedestrian delay. It was observed that travel times were significantly higher during the reduced maximum cycle length based on before and after analysis. The authors concluded that the solution of maximum cycle length reduction did not interfere with other goals for the corridor.

Kergaye et al. (2010) compared the performance of two systems: time-of-day actuated-coordinated signal and the SCATS installed in Park City, Utah. It was found that SCATS was better than the actuated system when assessed through both the “before-after” and “off-on” approaches. The before-after analysis was conducted to evaluate the traffic performance when a new traffic control system is deployed. The “off-on” method was implemented to assess the two traffic control strategies on the same system. The results were more favorable if the off-on approach was used. Monsere, Eshel, and Bertini (2009) reported on the results of a before-after evaluation of the performance of a System-Wide Adaptive Ramp Metering (SWARM) and pre-time system that was implemented in Portland, OR. Statistical analyses were made to evaluate performance matrices, including vehicle miles traveled (VMT), vehicle hours traveled (VHT), and delays. Mixed results were produced when comparing the performance metrics to the pre-timed operations. More recently, a before and after analysis was conducted on a traffic corridor in Albany, NY, which found that the adaptive traffic control system, Adaptive Control System Lite (ACS Lite), is effective to improve traffic within the adaptive control system, but increases delays at the boundary intersections (Ban et al. 2014).

Clearly, adaptive control is not always the best choice for a given corridor or intersection. There are certain requirements and preconditions to deploy it, such as arterial networks with various traffic demands. Previous studies used before and after analysis to demonstrate the advantages of adaptive signal control, which has two potential issues. First, there lacks a “big-picture” assessment on whether adaptive control should even be considered, provided the characteristics of the corridor (such as delays, volumes, etc.) and the needed resources (such as hardware, software, communications, etc.). Second, the existing before-and-after based methods rely on simple statistical analysis, which may not be able to use the massive amount of data that are increasingly collected and available to transportation and traffic engineers.

In this project, the aim was to develop two methods: a *qualitative* analysis method to provide the “big picture” assessment of adaptive control, and *quantitative* analysis method to provide in-depth analysis using large amount of traffic and other related data sets. The qualitative analysis was developed based on the review of the best practices of adaptive signal control system deployment in the nation. The quantitative analysis methods are based on big data analytics methods to take advantage of the rich data sets traffic management agencies are collecting or having access to right now.

Big data management is a recently developed technique that aims to better utilize massive amount of data sets accumulated in many engineering and science disciplines. Big data is usually characterized by “3V” or “4V” (Beyer and Laney 2012), which stands for:

- Volume **-** the size of the data set should be big enough.
- Velocity **-** the data has to be dynamic in the sense that there is always new data coming in and old data becoming obsolete (for example, traffic detector data collected every 30 seconds).
- Variety **-** there are different types of data coming from different sources (for example, data that can be collected from a transportation corridor, including volume, speeds, occupancy from detectors, travel time from travel time sensors, weather information, special events, among others).
- Veracity **-** inherently the data is incomplete and/or contains errors that need to be carefully dealt with.

It is clear that big data matters because it is not only “big” in terms of size, but also dynamic, heterogeneous, and erroneous. The key philosophy in big data analysis methods is for data “to speak.” That is, one only cares about the correlations among data elements (i.e., the “what”), but not the underlying reasons behind the corrections (i.e., the “why”). There have been successful applications of big data analysis methods, mainly for decision making purposes, e.g., when is the best time to buy an airline ticket (McAfee, A. et al. 2012) and Google’s epidemics prediction online tool (Google 2015).

In transportation and traffic engineering, the data generated in real time with large quantities and collected from sensors, devices, video/audio, network, log files, transactional applications, web, and social media are naturally big data. Research has been emerging on using big data methods based on the massive amount of traffic-related data for the operations and planning of transportation systems. With the help of big data methods, researchers and practitioner can make better transportation decisions such as optimizing operations, developing rational infrastructure plans, and examining the distribution and patterns of large public events (Ozbay et al. 2014).

In this project, data analysis methods were introduced, such as regression analysis methods and support vector machine (SVM), to help conduct the quantitative analysis. In particular, using SVM, “good” signal performance (i.e., level of service [LOS] A-C) can be distinguished from “bad” signal performance (LOS D-F), based on multiple traffic measures. Two ways were proposed to correlate the before and after data using SVM, from which to develop the quantitative decision making tool for deploying adaptive control systems. Discussions were provided regarding the limitations of the proposed decision tool and future research directions. Limitations and research needs for big data analysis methods were also presented. The proposed decision making tools provide a two-stage decision making process for decision-makers to decide where adaptive control systems should be deployed. In the first stage, the qualitative tool was used to have a high level analysis, based on traffic and required resources, to obtain a quick assessment regarding whether adaptive control should even be considered. In the second stage, detailed data and analysis was conducted using the big data analysis method to determine whether adaptive control can be really beneficial compared with existing control systems (such as actuated control systems).

2 Review of Current Adaptive Signal Control Technologies

Adaptive signal control technologies adjust when green lights start and end based on the current traffic conditions, demand, and system capacity to accommodate current traffic patterns to promote smooth flow and ease traffic congestion. In the United States, several adaptive systems are available from multiple vendors. This chapter reviews how adaptive signal control systems perform, including the following:

- Investigating case studies in North America and several other countries.
- Identifying and describing the characteristics and performance of alternative adaptive signal control systems.
- Identifying the measures of effectiveness of adaptive signal control systems.

2.1 Alternative Adaptive Traffic Signal Control Systems

Adaptive traffic signal control is not widely deployed now but receiving more and more attention throughout the United States. A synthesis report (Stevanovic 2010) described the state of practice in deploying adaptive traffic control systems in North America with an overview deployments around the world. Zhao and Tian (2012) provided a comprehensive overview of the state-of-the-art and state-of-the-practice of adaptive traffic control system. Shelby and Bullock (2008) provided an overview of the ACS Lite system with field evaluations. Fehon and Peters (2010) compared and contrasted the systems that have been successfully installed in the U.S. and discusses their advantages and disadvantages. Through several studies, it was determined that myriad benefits were demonstrated after the installation of these complex systems. Many vendors currently manufacture their own versions of software. Meanwhile, there are even more methods of analyzing the successes of the software packages in various settings and situations.

The measures of effectiveness (MOEs) per system can vary greatly; so extensive research has been done to ensure that a potential system has the capabilities to accommodate demand in its respective area of deployment. These measures range from before-after studies, benefit-cost ratios, percent reduction in stops, among others. Although there is no one indicator that can prove a system is superior to another, there are ways to gauge the efficiency, including examining certain characteristics of each system.

The operational goals involve varying degrees among different adaptive control systems as shown in Table 1.

Table 1. Adaptive Traffic Signal Control system and Respective Operational Goal

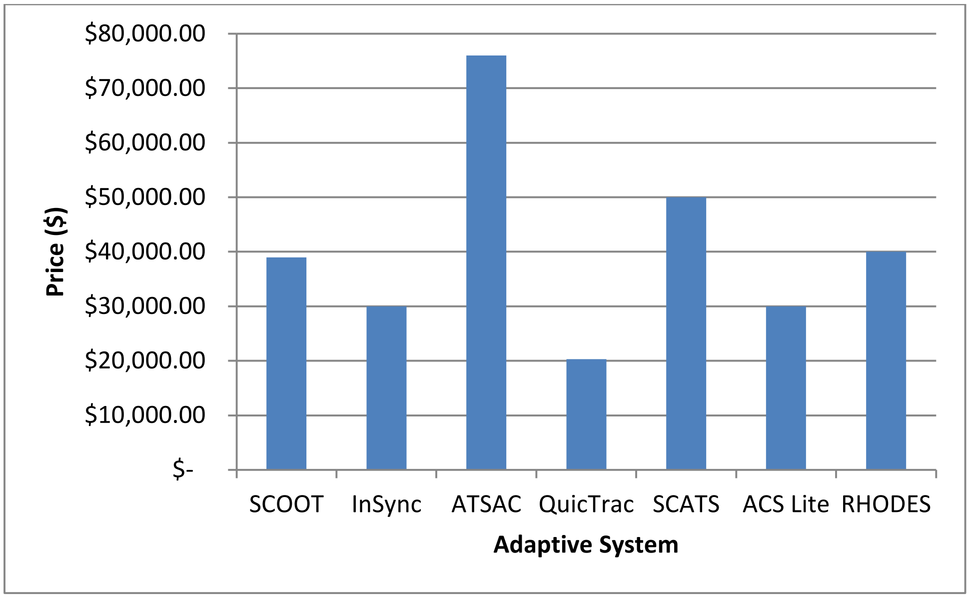
Based on Stevanovic (2010)

Adaptive System	Goal
ACS-Lite (by FHWA and Siemens)	Adjusts timing on a cycle basis
Adaptive Control Decision Support System (ACDSS)	Minimize delay, manage queue by diamond interchange control.
Automated Traffic Surveillance and Control (ATSAC)	Adjusts timing on a cycle basis
InSync (by Rhythm Engineering)	Minimizes queues and delay time
QuicTrac (by McCain Engineering)	Minimizes delay, congestion via local volume collecting data controllers.
Real Time Hierarchical Optimized Distributed Effective System (RHODES)	Responds to natural behavior of traffic flow
Split Cycle Offset Optimization Techniques (SCOOT)	Minimizes delay with relative importance on stop
Sydney Coordinated Adaptive Traffic System (SCATS)	Minimizes stops, delay, and travel time
TranSuite	Minimizes delay, stops, and travel time

These systems are typically expensive, and the installation itself is costly. An approximated price breakdown is presented in Figure 1. For the purposes of the benefit-cost analysis, six models are compared, including SCOOT, SCATS, InSync, QuicTrac, ACS Lite, and ACDSS. The average cost to install the system per intersection ranges from $20,000 to nearly $80,000, which is quite expensive compared with existing fixed-time or actuated signal control systems. ACDSS is a relatively new system, and its cost data are not readily available yet. The cost is an important factor that needs to be fully considered when upgrading existing traffic control systems to adaptive traffic control system. The remainder of this section provides some review and analysis for these six systems.

Figure 1. Average Cost per Intersection

Source: Jesus (2011)



SCOOT. The Kernal software plays an important role in the SCOOT system. It is standard with each installation. Additional software, Urban Traffic Control (UTC), links SCOOT's Kernal to on-street equipment and provides the user interface. It is specific to each supplier. SCOOT MMX provides facilities to prioritize pedestrians at junctions. Table 2 provides the benefits of deploying SCOOT in Toronto, Canada (SCOOT 2014).

Table 2. Statistics on Toronto Deployment

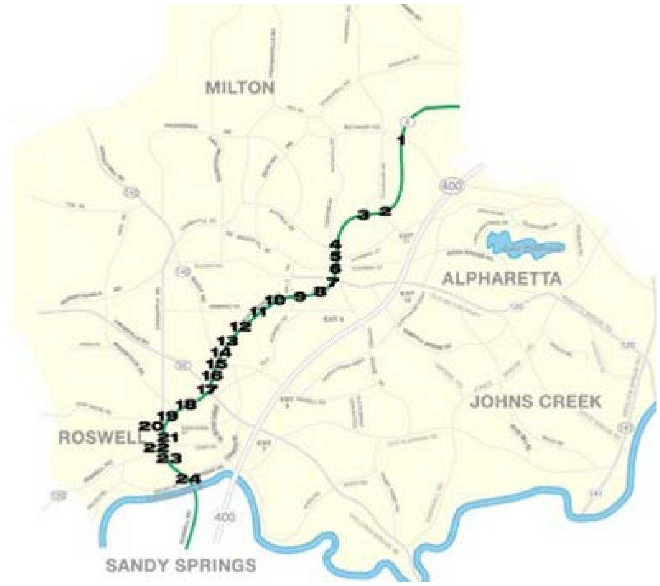
Source: SCOOT (2014)

Category	Reduction (%)
Delay	17%
Stops	22%
Fuel Consumption	5.7%
Hydrocarbon Emissions	5%

Roswell, GA has been building the SCOOT system since 2008. The system combines 38 traffic cameras and more than 60 traffic lights that can all be controlled from a control room in Roswell. According to Brent Srory (2011), SCOOT is an appropriate strategy because the area has high levels of nonrecurring congestion, such as incidents and special events, and with fluctuating traffic demand (Figure 2).

Figure 2. Map of Installed Signal in Roswell

Source: Copsey (2014)



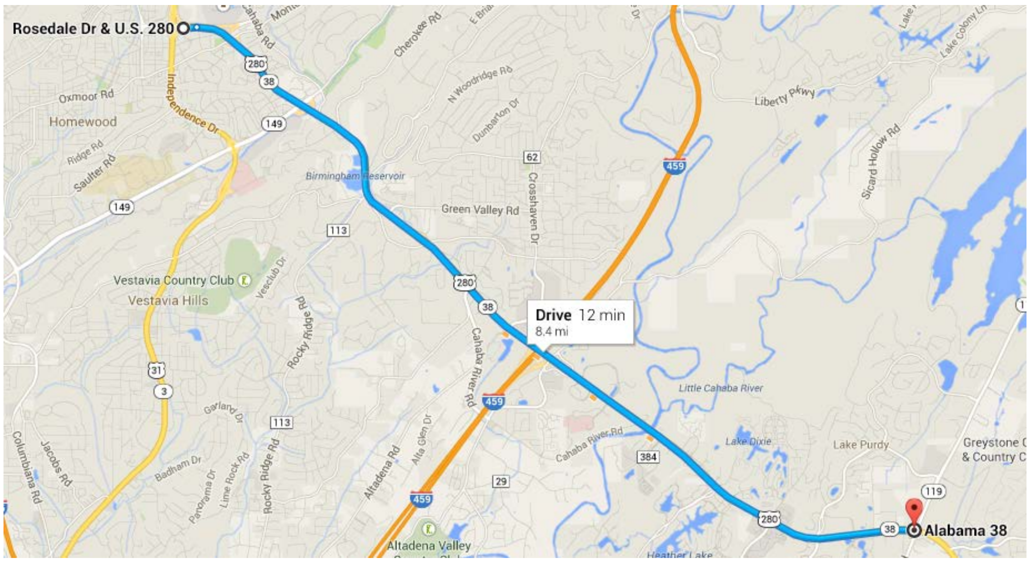
SCATS. The Sydney Coordinated Adaptive Traffic System (SCATS) is an area traffic control (ATC) or urban traffic control (UTC) system. SCATS manages groups of intersection rather than changing individual intersections in isolation. The system was developed in Sydney, Australia in the 1970s. The majority of signalized intersections in Australia today are SCATS-operated. It was also used in New Zealand, Hong Kong, Shanghai, Amman, Tehran, Dublin, and other places.

In the United States, SCATS has been installed in White Plains, NY; Oakland County, MI; Bellevue, WA; and Sunnyvale, CA. According to Wang et al. (2013), SCATS has shown great improvement in the Oakland County, where 28 intersections were studied with the new technology. SCATS decreased the travel time by 6.7%, number of stops by 26.5%, queue length by 17.5%, total travel delay by 19%, fuel consumption by 5.1%, and increased the average travel speed by 7.0%.

SCATS was deployed on Tarrytown Road in the city of White Plains in New York. Tarrytown Road is a major commuter arterial that carries approximately 50,000-60,000 vehicles daily. The traffic demand fluctuates daily with serious congestion during peak hours. According to Lardoux et al. (2014), there is 15% reduction in travel times and 25% reduction in number of stops in the morning peak hour when the SCATS is deployed. In midday and afternoon, the number of stops decreased more than 30%.

Alabama has selected SCATS to reduce congestion at intersections on U.S. 280 (see Figure 3). The plan is to modify 26 signalized and non-signalized intersections along 8.2 miles of the highway in Jefferson and Shelby counties. Results showed that the adaptive traffic system has reduced overall motorist travel time by six to eight minutes (RPCGB 2014).

Figure 3. Corridor Affected by the Adaptive System (Rosedale and U.S. 280 to Doug Baker Rd in Alabama)



SCATS has also proved to be successful in Park City, Utah, with improvements made at 14 intersections during the afternoon and midday peaks. Conditions for the Park City test were under fair weather and dry pavement conditions. Based on the literature, SCATS produces higher cycle lengths than the fixed-time system. Moreover, SCATS tends to be set up with the preference to serve mainline over side street movements to improve mainline progression.

QuicTrac. The QuicTrac system can introduce robust timing archive features, customized reports, and centralized document control. The benefit includes identifying trends and visualizing measures of effectiveness with accurate traffic counts displaced on charts (McCain 2013). QuicTrac collects data from a modest number of field detectors, loop or video, requiring only enough obtaining a reasonable sampling of speed along the corridor. Data is sent to the QuicTrac software module of central control software, and analyzed using specific algorithms, calculating optimum cycle lengths, splits and offsets based on prevailing traffic conditions.

The benefits of QuicTrac are illustrated Figure 4 and Table 3. Data was collected from San Marcos Boulevard in California. It is the second busiest arterial in San Diego County, with an average daily traffic volume of 22,000- 46,000. The corridor intersects a major highway and is lined with businesses and schools. The results show significant reductions in terms of delays and stops, and moderate to minor reductions in fuel consumption and emissions.

Figure 4. San Marcos Boulevard (yellow) with intersecting Ronald Packard Pkwy (orange)

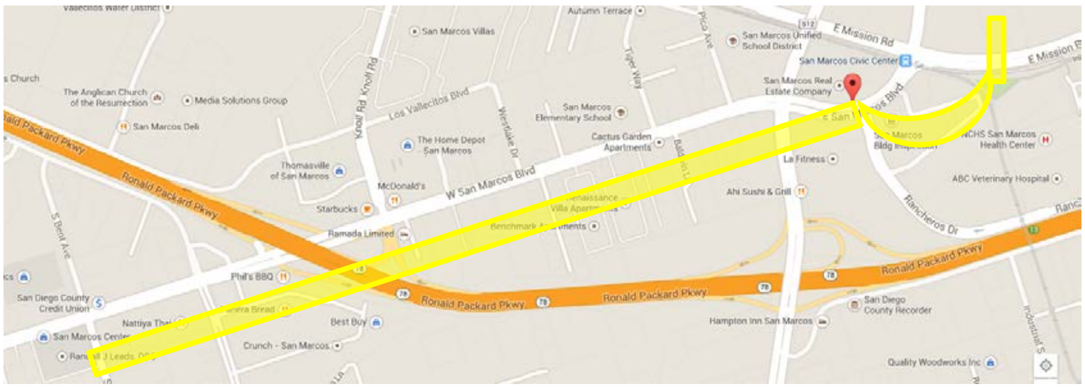


Table 3. Statistics along San Marcos Boulevard

Source: McCain (2015)

Category	Reduction (%)
Delay	46%
Stops	39%
Fuel Consumption	8%

InSync. Widely deployed in the United States, InSync uses artificial intelligence to optimize traffic signals at individual intersections and coordinates signals along arterial corridors to reduce traffic congestion. Case studies have been conducted to demonstrate how well the InSync System works. One of the studies was conducted in Pinellas County, FL. After installing the InSync System, there was a 37% reduction in stops, a 12% reduction in travel time, a 24% reduction in delay, a 16% reduction in emissions, a 12% increase in average speed, and a 9% reduction in fuel usage (RHYTHM 2012). Another study in Upper Merion, PA was conducted to see how effective the InSync system is. By using video detection and its built-in artificial intelligence, InSync adapts signalization to actual demand, allowing queues of vehicles to clear quickly and completely every time. Table 4 shows significant reductions in terms of travel times, delays, stops, and increase of travel speeds.

Table 4. Statistics for Upper Merion, PA

Source: RHYTHM (2011)

Category	Percentage (%)
Reduction in Travel Time	26%
Reduction in Stops	21%
Reduction in Delay	34%
Increase in Average Speed	35%

The InSync system was deployed on 10th Street in Greeley and the QuicTrac system was deployed on US 25 in Woodland Park in Colorado. A report from CDOT (CDOT 2012) summarized the results of the evaluation conducted regarding the implementation of these two different adaptive traffic signal control systems in Colorado. Although the installation cost of InSync system is much expensive than QuicTrac system, the Insync system would have saved the agencies more than $ 9.2 million over the rist 20 years of operation which outweighs the $ 5.7 million saving of QuicTrac system. Table 5 compares InSync and QuicTrac.

Table 5. Comparison of System Benefits

Source:Colorado Department of Transportation (CDOT 2012)

Category	InSync System		QuicTrac System	
	Actual Project	Minimal Project*	Actual Project	Minimal Project*
Number of Intersections	11		8	
Daily cost saving (corridor)	$3,789		$2,567	
Annual cost saving (corridor)	$1.326 million		$898,500	
Install costs (corridor)	$905,500	$375,000	$176,300	$162,400
Daily cost saving (per intersection)	$344		$321	
Annual cost saving (per intersection)	$120,500		$112,300	
Install costs (per intersection)	$82,300	$34,000	$22,000	$20,300
Benefit to cost ratio	1.58	3.79	5.64	6.10
10-year projected savings	$4.2 million	$4.7 million	$2.8 million	$2.8 million
20-year projected savings	$9.2 million	$9.7 million	$5.7 million	$5.7 million
AADT (CDOT data near middle of corridor)	26,500 vehicles		22,500 vehicles	
Daily cost saving per user	$0.14		$0.11	
Annual cost saving per user (assume 350 day use of road)	$49.00		$38.50	

ACS Lite (Adaptive Control Software Lite) is considered a closed adaptive loop system. In a closed loop system, a master communicates with locals, which collect data from the local detectors and the additional system detectors. ACS Lite works by collecting data, compares the collected data to normal coordinated timing plans, performs an analysis on this, and then implements phase split adjustments. ACS Lite requires stop line detectors, separated by individual lane-by-lane monitoring, although if lanes are serving the same phase/movement, they may be tied together. Stop line detectors monitor volume and occupancy on green, and the processing logic accounts or adjusts for the detector length. ACS Lite is very flexible with detector technologies, as it has been tested with various ranging from: inductive loops, video, wireless detectors, to radar detectors. The SCATS system works very similar to ACS Lite with the exception that this system does not use the pre-timed signal schedule to compare it to real time traffic like ACS Lite does. ACS Lite would be preferred if the installation cost was the most important aspect of the project at hand. The central control system is not required for ASC Lite; it can be controlled remotely through the use of a laptop device.

The first deployment of the ACS Lite system was in Gahanna, OH, a suburb of the city of Columbus. The city has a Closed Loop System (CLS) along Hamilton Road with I-270 to the south and Clark State Road to the north, as shown in Figure 5. Hamilton Road serves as a connection between the city of Columbus to the north and I-270 to the south. Hamilton Road does not serve as a major route and is classified as a principal arterial. Additional results are provided in Table 6.

Figure 5. Deployed Area in Gahanna, OH

Source: FHWA (2006)

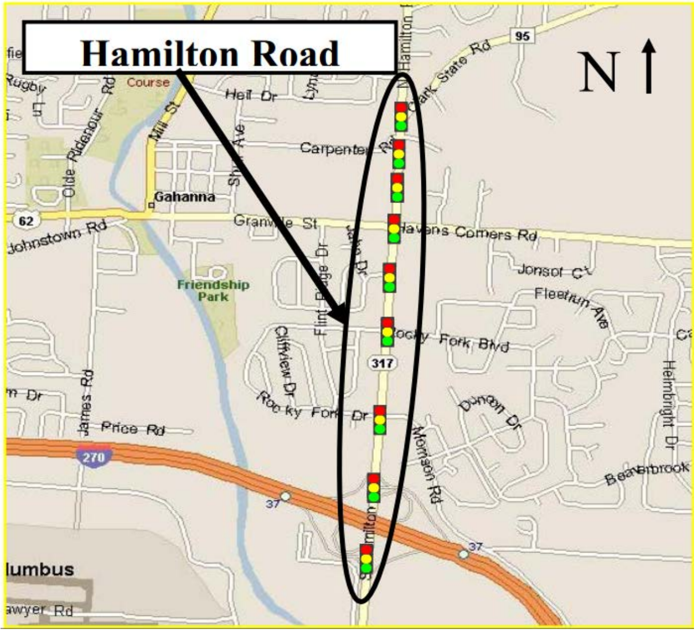


Table 6. Results for Hamilton Road

Source: FHWA (2006)

	Before (per veh)	After (per veh)	Savings (per veh)	Peak Hours (all vehs)	Peak Hours Savings
Total Delay (hour)	0.03761	0.03758	0.00003	0.15588	$1.89
Total Stops	3.5	2.9	0.6	3117.6	$43.65
Fuel (Liters)	0.390	0.373	0.017	89.287	$53.08
Peak Hours Benefit	$98.61				
Daily Benefit	$340.03				
Annual Benefit	**$88,500.00**				

NYSDOT upgraded the actuated traffic signal control system on Wolf Road in Albany, NY to ACS Lite (Ban et al. 2014). The Wolf Road corridor is a destination corridor with very heavy demands during peak hours. The results showed that after ACS Lite was installed, the delays at the boundary intersections increased dramatically, while the delays of the intersections within the corridor decreased slightly. These results indicate that for a heavily congested corridor (such as the Wolf Road Corridor), ACS Lite can potentially improve traffic flow within its own system. However, this may be achieved by “metering” (i.e., restricting) flow into the system, thereby generating large delays/problems at the boundary intersections. Obviously, this metering effect would depend on the specific adaptive control system as well as the actual traffic conditions of the corridor system. In addition, software issues were discovered with the specific ACS Lite control software packages used in the Wolf Road project, which also exacerbated the issues at the boundary intersections of the corridor (Ban et al. 2014).

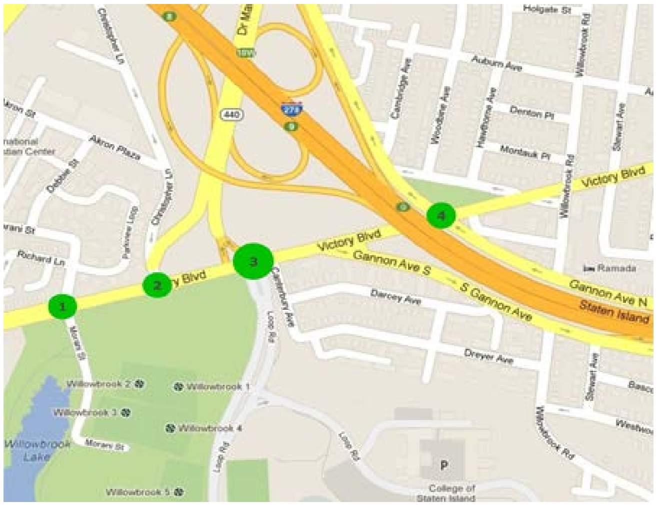
ACDSS (Adaptive Control Decision Support System) was developed for NYCDOT by KLD Associates, Inc., with support from NYSERDA. It is an advanced real-time, signal optimization system that integrates online simulation with actual field traffic controllers and detectors. It can provide optimized signal plans for both over- and under-saturated traffic. ACDSS uses the just-in-time (JIT) microscopic traffic simulation model AIMSUN because it can run multiple simultaneous instances at high speed. ACDSS enables several algorithms to be incorporated as switchable plug-ins. The concept of Signal Optimization Algorithm Repository, which enables delay minimization, diamond interchange control, and queue management, supports regional multi-objective and it can incorporate any state-of-the-art algorithm (ACDSS 2013a). ACDSS requires volume and occupancy data in approximately every 30 seconds. A Web service interface is responsible for retrieving data from sensors. The system supports autonomous mode and 24/7 operations. It can also be operated based on time of day, day of week, or date of month schedules.

ACDSS has been successfully deployed in Midtown Manhattan where a closely spaced signalized grid system is present with highly over-saturated traffic. There are heavy pedestrian volumes and frequent intersection spill-backs due to the overflow queues. The implementation of ACDSS started on July 11, 2011, covering 110 square block zone in central business district of Midtown Manhattan. It has resulted in a 10% improvement in speeds in this area (ACDSS 2013b). To guarantee smooth pedestrian and bicycle movements, NYCDOT decided to maintain the 10% speed improvement.

Victory Boulevard is a major east-west arterial road that runs 8 miles on Staten Island and is characterized by heavy communing traffic and the traffic entering and exiting the College campus (Figure 6). It is a good candidate for adaptive control because the traffic demand varies daily due to the class schedule. ACDSS was deployed in a 0.5-mile stretch of Victory Boulevard from North Gannon Ave to Morani St. including four intersections. There were significant improvements in arterial performance after deploying ACDSS, including 8% reduction in fuel consumption, 42% reduction in average stops, 30% reduction in average delay, 20% improvement in speeds, and 7% improvement of throughput (ACDSS 2013c).

Figure 6. Victory Boulevard Deployment Along Four Intersections

Source: ACDSS (2013c)



This review showed that the majority of system deployments has significant improvements in traffic delay, number of stops, and fuel consumptions than traditional pre-time signals, with some noticeable exceptions (such as the Wolf Road ACS Lite system in Albany, NY). Regarding deployment costs, QuicTrac was the lowest, while ATSAC was the highest. The actual costs vary significantly depending on the level of detection needed. The high cost for SCOOT was probably due to the large number of detectors required (Zhao and Tian 2012).

2.2 Measures of Effectiveness

Adaptive traffic signal control systems aim at achieving multiple objectives. There have been many attempts to measure the performances of adaptive traffic signal control systems. Some of the studies suggested that the impacts on performance could be different according to site-specific issues and selected performance metrics (Hunter, Wu and Kim 2005; Hunter et al. 2012; Hunter, Wu and Kim 1978). These studies developed procedures to access the overall impacts of adaptive signal control on arterials, including travel time, side street delays, and system-wide performance based on the data collected from probe vehicles. Other studies have accounted for the performance of side streets (Abdel-Rahim, Taylor, and Bangia 1998; Hunter, Wu, and Kim 2010; Peters et al. 2008), such as side street delay and delays for major turning approaches. The most typical measurements of performance are listed as follows.

Route Travel Time

The most common evaluation approach is to measure route travel time. Travel times are always measured as the time difference at which each signalized intersection is encountered and the time to reach the stop line. Basically, there are two types of approaches for measurement of travel time: GPS probe vehicle and vehicle –identification technology. The probe car techniques were well demonstrated in the studies from Robertson, Hummer, and Nelson (1994). The advanced technologies such as GPS probes and Bluetooth can be used to measure the travel time effectively. When collecting travel times, some of the issues need to be considered. It is normally assumed the traffic conditions are stable during the survey period. Travel times are typically collected during peak hours while it may limit the capacity of adaptive signal technology since it is most suitable when traffic demand is unpredictable. In addition, the number of runs using probes should be significant. NCHRP Report 398 (Lomax, Turner, and Shunk 1997) gave reference on the suggested sample size for data collection. They recommended sample sizes ranging from 2 to 14 individual test runs based on the desired level of confidence. Vehicle re-identification technology is able to provide 24/7 information but lack of detailed information on individual vehicle performance between the end points of the trip.

Travel Time Reliability

Travel time reliability is an important measurement of network performance. The concept of travel time reliability is defined interchangeably with travel time variability in the transportation research literature. Most reliability measures are calculated from the day-to-day distribution of travel times on a particular route, that is, the variability in travel time vehicles experience on a particular time-of-day (TOD) and day-of-week (DOW) period over a longer time period. A comprehensive overview of travel time reliability measures can be found in the research from Lomax et al. (2003).

Delay

Traffic delay and traffic count information are usually studied with traditional manual observation techniques. Floating car data can provide detailed information during the periods when data were collected. These techniques can be effective, but cannot be used for long periods of time because of the cost and staffing concerns. So they are usually collected at selected high-volume intersections. Other data sourced from GPS loggers, videotaping, high-resolution phase timing and detection data are available now to reduce the manual effort and expand storage capabilities. They can operate 24-hours per day, which enables the researchers to access the performance of adaptive signal during off-peak hours or other times when data were not collected.

Traffic Volume

Traffic volume is defined as the total number of vehicle traveling from the origin to the destination during a given period of travel time. It is the direct measurement of throughput. There are two types of technologies that could measure the traffic volume, based on point sensors and vehicle re-identification techniques.

Derived MOEs

The performance of adaptive traffic signal could also have impacts on society. The corresponding measurements, such as fuel use, emissions, and benefit/cost ratios are typically used to estimate the impacts. Fuel use and emission could be estimated from GPS probe vehicle trajectories. Benefit/cost analysis could justify if the benefits of the project outweigh the costs of implementation over a significant period of time by computing the Net Present Value and benefit/cost ratio according to economic principles.

After collecting all these data, the before and after studies could be used to evaluate the network performance where “before” study represents traditional traffic signal control conditions and “after” study corresponds to adaptive signal control technologies. A before and after study using Empirical Bayes (EB) approach was recommended in Highway Safety Manual (HSM) (AASHTO 2010). They examined the impacts of adaptive signals at urban intersections. However, these types of studies are criticized as not being completely representative of a corridor’s performance. The data are always collected under “before” conditions and “after” conditions separately so that the traffic volume and pattern are not identical. Other variables can impact the traffic flow between those times. Rather than dealing with issues of a “before and after” study, several studies have begun to study performances using on/off techniques. The network performance are compared with the studied system active and while it was inactive. Stevanovic et al. (2009) and (Fehon et al. 2012) have applied on/off techniques in simulation studies and evaluations.

Table 7. Identification of Data Sources and Measures of Effectiveness for Operational Objectives

Source: Gettman et al. (2013)

MOEs	Data Sources	Operational Objectives (Fehon et al. 2012)
• Smooth flow	• Import travel time data from vehicle re-identification scanners • Import trajectory data from GPS probes • Import high-resolution signal timing and detector data	• Route travel time • Route travel delay • Route average speed • Link travel time, delay • Number of stops per mile on route • Percent arrivals on green, by link • Platoon ratio, by link
• Access Equity	• Import high-resolution signal timing and detector data	• Green-Occupancy-Ratio • Min, Max, and Standard Deviation of Green-Occupancy-Ratio • Served Volume/Capacity ratio by movement
• Throughput	• Import count data from tube counter file	• Total traffic volume on route • Time to process equivalent volume
• Travel time reliability	• Import travel time data from Bluetooth scanner • Import trajectory data from GPS probe • Import high-resolution signal timing and detector data	• Buffer time • Planning time • Minimum, maximum, and standard deviation of platoon ratio • Minimum, maximum, and standard deviation of percent arrivals on green

These measures of effectiveness (MOEs) could be used to evaluate the performance of a traffic control strategy. The typical MOEs includes smooth flow, access equity, throughput, and travel time reliability. Table 7 summarizes the MOEs and data sources for each operational objective. The operation objectives for each MOE are listed separately.

3 Guideline of Deploying Adaptive Traffic Signal Control System

Guideline was developed to help conduct qualitative analysis of adaptive traffic signal control deployment. The decision tree in Figure 8 was developed for this purpose to help traffic engineers and decision-makers determine whether adaptive control is best suited for a given traffic corridor and/or intersections than existing control systems. The key to selecting an adaptive signal system is to identify its operational objectives and where it is effective.

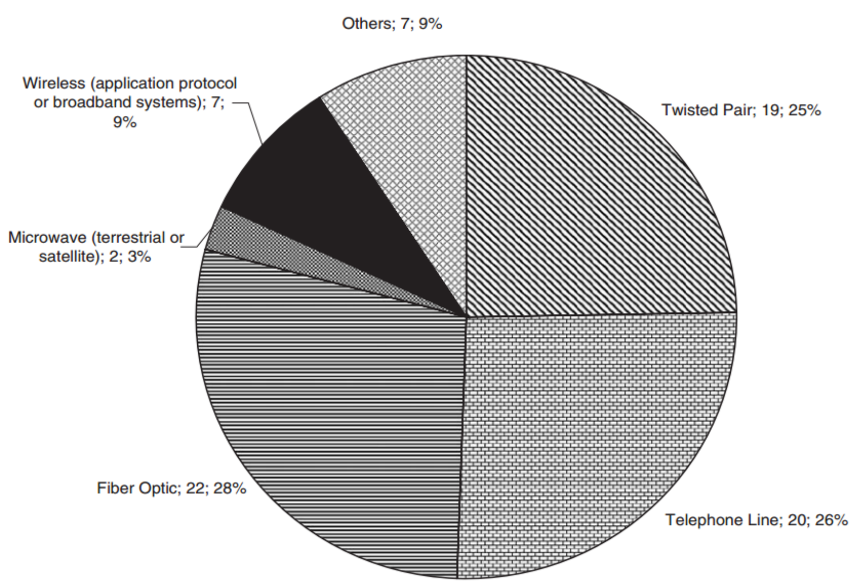
Adaptive signal should be installed in the environment in which they can contribute to reducing traffic congestion and improving traffic operations (Stevanovic 2010). A survey reported that 80% of the interviewed agencies deployed adaptive signal in the network with speed limits between 30 and 45 miles per hour. Another main benefit of adaptive signal control is that it can improve travel time reliability. Thus, it indicates that the conventional signal timing needs to be updated when serious delays and unreliable travel times occurred at an intersection. In addition, the network layout where an adaptive signal is deployed will also influence the performance of adaptive signal. It is observed that the significant advantages could be obtained when the adaptive signal are deployed on a through corridor at a signalized arterial route and for closely spaced intersections. Statistics showed that 42% of all agencies have deployed adaptive signal control solely on arterial networks and 10% deployed it on grid networks, which are more typical in European cities (Stevanovic 2010). Adaptive signal can also react to the unexpected changes or events in traffic conditions, such as high, various, and unpredictable traffic demand, crashes, and special events. By implementing the updated signal timing in real time, travelers are delivered improved service.

According to Hicks and Carter (2000), cost is the major obstacle to deploy adaptive signal control. Costs include licensing, warranty, training and support, hardware, and maintenance (USDOT 2013). The cost of various adaptive signal control systems ranges between $20,000 and nearly $80,000 per intersection depending on the current infrastructure, requirements of communications, and detections of the certain systems. Mostly replacements of the local intersection hardware and software, or even installing new communication infrastructure may accompany with the deployment of the adaptive signal control system, which would increase the cost largely. Adaptive traffic signal control system needs accurate vehicle detection and relies heavily on the quantity and quality of traffic data available from detectors.

A survey showed that most of the agencies use a mixture of various detection technologies for their adaptive signal control systems. Approximately 93% of the agencies use inductive loops, almost half (43%) also use video detection. Nearly one-fifth (18%) of the agencies use radar detection, whereas only 9% use other types of detection not contained in any of these three major technologies (Stevanovic 2010). Typically, most systems require at least one detector per lane per signal phase. The way in which signals are interconnected in network impacts the operation of adaptive signal control system. Figure 7 shows that around 80% of all agencies use three major types of communication media (twisted pair, telephone lines, and fiber optic cables) to communicate between the central system and field controllers. Centrally controlled systems usually cost between $40,000 and $80,000 per intersection (Malekm, Denney, and Halkias 1997).

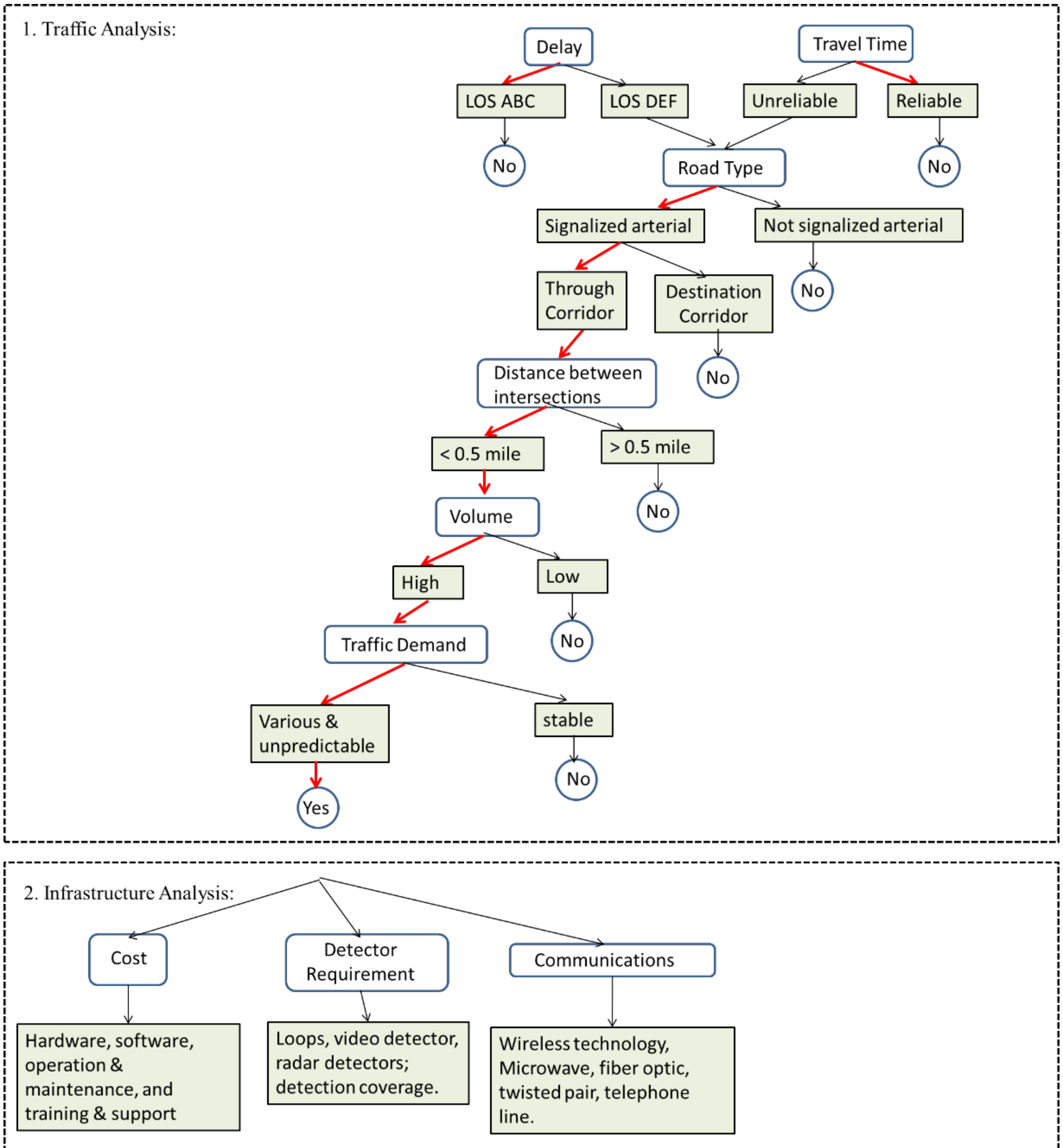
Figure 7. Communication Media between Central System and Field Controllers

Source: Stevanovic (2010)



Based on the state of the practice review and discussions with traffic signal control experts, the decision tree in Figure 8 represents a layered decision process on where and under which environments the adaptive signal control system is recommended to relieve traffic congestion and provide smooth traffic flow. Layer 1 lists the *traffic analysis* to install adaptive signal, including considerations of corridor volumes, delays, travel times, road type, and signal spacing. Layer 2 indicates the *infrastructure analysis* that needs to be considered, including cost, detector requirement, and communications requirement. It can provide the hardware, software, communication requirements for installing adaptive traffic signal control system, as well as the overall installation costs.

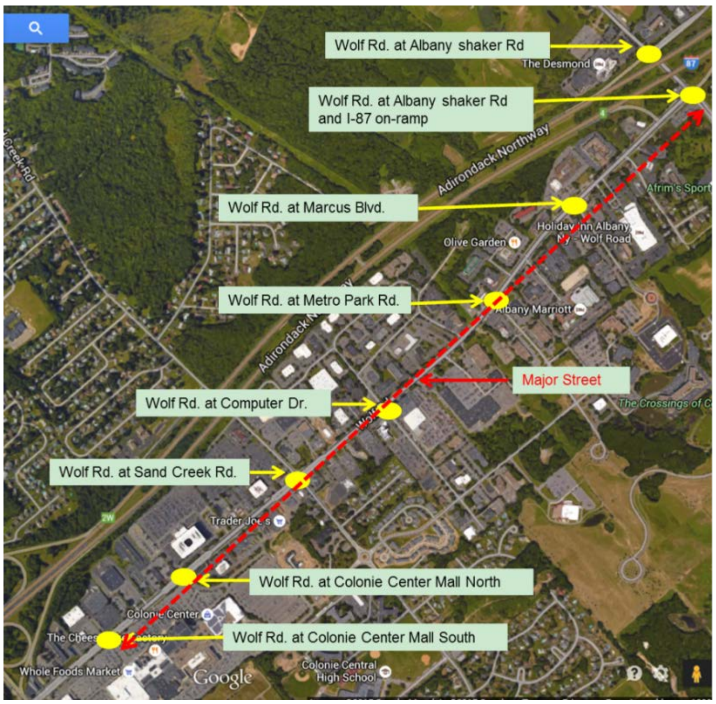
Figure 8. Decision Tree for Adaptive Signal Control



4 Building the Database for Quantitative Analysis

The quantitative analysis method was developed using data collected from the Wolf Road corridor in the Albany, NY area (Ban et al. 2014). The big data analysis methods were also developed based on the Wolf Road data set. This chapter describes the database system that archives the Wolf Road data. Figure 9 depicts the Wolf Road corridor, which is a major arterial that connects to Interstate 87. Wolf Road experiences serious congestion due to the large number of restaurants, retailors, and shopping malls along the corridor and the heavy commuter traffic at peak hours.

Figure 9. Deployment Locations of Actuated and Adaptive Traffic Control System on Wolf Road

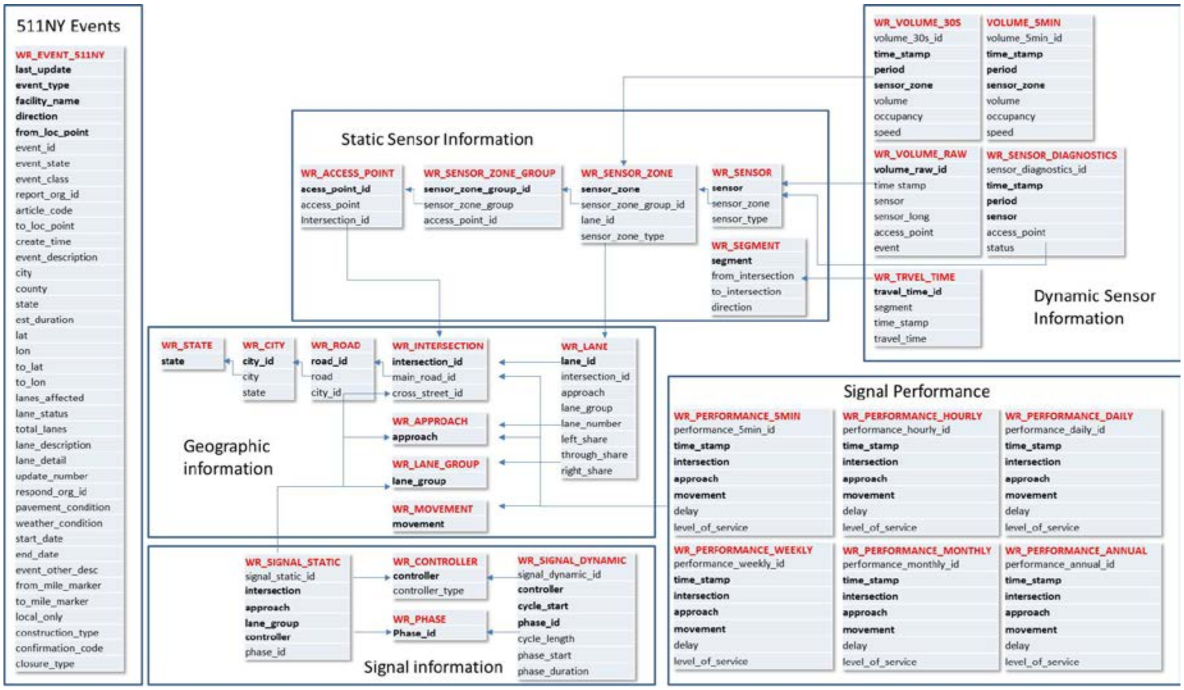


The Wolf Road database is constructed in MySQL, with SNAPS_WR as the database name. All table names are listed in Table 8. More details of each table and the schema are provided later in this section. Figure 10 illustrates the database schema layout. The name, type, and description of each column in each table are shown. The primary keys of the tables are highlighted in bold style.

Table 8. Table Names

WR_STATE
WR_CITY
WR_ROAD
WR_INTERSECTION
WR_APPROACH
WR_LANE_GROUP
WR_MOVEMENT
WR_LANE
WR_ACCESS_POINT
WR_SENSOR_ZONE_GROUP
WR_SENSOR_ZONE
WR_SENSOR
WR_SENSOR_EVENT
WR_SEGMENT
WR_VOLUME_RAW
WR_SENSOR_DIAGNOSTICS
WR_VOLUME_30S
WR_VOLUME_5MIN
WR_TRAVEL_TIME
WR_CONTROLLER
WR_PHASE
WR_SIGNAL_STATIC
WR_SIGNAL_DYNAMIC
WR_PERFORMANCE_5MIN
WR_PERFORMANCE_HOURLY
WR_PERFORMANCE_DAILY
WR_PERFORMANCE_WEEKLY
WR_PERFORMANCE_MONTHLY
WR_PERFORMANCE_ANNUAL

Figure 10. Wolf Road Database Schema Layout



4.1 Geographic Information

The geographic information block includes all location-related tables in the database, such as state, city, road, intersection, approach, lane group, movement and lane. Table 9 gives the name, data type, and definition of each column in each table.

Table 9. Tables of Geographic Information

WR_STATE		
state	varchar(20)	state names, including: NY
WR_CITY		
city_id	int	ID of the city
city	varchar(40)	city name, including: Albany
state	varchar(20)	state location of the city
WR_ROAD		
road_id	int	ID of the road
road	varchar(40)	road in the Wolf Road corridor, including: Wolf Rd, Old Wolf Rd, Albany Shaker Rd, Marcus Blvd, Metro Park Rd, Computer Dr, Sand Creek Rd, Colonie Center North, Colonie Center South
city_id	int	city ID of the road
WR_INTERSECTION		
intersection_id	int	ID of the intersection
main_road_id	int	The road ID of north-south direction
cross_street_id	int	The road ID of east-west direction
WR_APPROACH		
approach	varchar(20)	Four directions, including: NB, SB, EB, WB
WR_LANE_GROUP		
lane_group	varchar(20)	lane group names, including: L, T, R, LT, TR, LR, LTR
WR_MOVEMENT		
movement	varchar(20)	movement names, including: L, T, R
WR_LANE		
lane_id	int	ID of the lane
intersection_id	varchar(40)	intersection ID of the lane
approach	varchar(10)	approach of the lane
lane_group	varchar(10)	lane group of the lane
lane_number	int	The lane index of the approach (left to right)
left_share	double	percentage of the left turn traffic volume for the lane, range: 0-1
through_share	double	percentage of the through traffic volume for the lane, range: 0-1
right_share	double	percentage of the right turn traffic volume for the lane, range: 0-1

4.2 Static Sensor Information

Sensys wireless detectors were used along Wolf Road. The static sensor information tables define all the objects in the detection system, including:

- *Access point* (WR_ACCESS_POINT) - devices installed in the field. It is the key link between SNAPS and remote detector networks under management.
- *Sensor zone groups* (WR_SENSOR_ZONE_GROUP) - a collection of sensor zones used for the purpose of supporting customized reporting or output requirements.
- *Sensor zones* (WR_SENSOR_ZONE) - a collection of sensors that perform a single function.
- *Sensor* (WR_SENSOR): a magneto-resistive wireless sensor to detect vehicle presence and movement.
- *Segment* (WR_SEGMENT) - the link segment for travel time collection, defined by a pair of sensor zones.

Table 10 gives the name, data type, and definition of each column in each table.

Table 10. Column in the Tables of Static Sensor information

WR_ACCESS_POINT		
access_point_id	int	ID of the access point
access_point	varchar(20)	ID of the access point, including: APCC482, APCC483, APCC485, APCC486, APCC488, APCC489, APCC494, APCC496
intersection_id	varchar(40)	intersection id of the access point
WR_SENSOR_ZONE_GROUP		
sensor_zone_group_id	int	ID of the sensor zone
sensor_zone_group	varchar(20)	sensor zone group name, including: I-87 SB Ramp, Albany Shaker Rd, Marcus Blvd, Metro Park Rd, Computer Dr, Sand Creek Rd, Colonie Center North, Colonie Center South
access_point_id	int	the access point ID that the sensor zone is associated with
WR_SENSOR_ZONE		
sensor_zone	varchar(20)	name of the sensor zone, e.g. WR@AS EBLN1
sensor_zone_group_id	varchar(20)	the sensor zone group of the sensor zone
sensor_zone_type	varchar(20)	type of the sensor zone, including: COUNT, ADVANCED, TT
WR_SENSOR		
sensor	varchar(20)	name of the sensor, e.g. 86A6
sensor_zone	varchar(20)	the sensor zone of the sensor
sensor_type	varchar(20)	type of the sensor, including: COUNT, ADVANCED, TT
WR_SEGMENT		
segment_id	int	ID of the travel time segment, range: 35-51
from_intersection	varchar(40)	starting intersection of the segment
to_intersection	varchar(40)	ending intersection of the segment
direction	varchar(20)	direction of the segment, including: NB, SB
WR_SENSOR_EVENT		
sensor_event	int	event id, range: 0-5
sensor_event_type	varchar(20)	name of the event type of the sensor, e.g. 0 for "off"; 1 for "on"

4.3 Dynamic Sensor Information

The sensor diagnostics, statistic, raw event, and travel time data, include:

- *Diagnostics* (WR_SENSOR_DIAGNOSTICS) - key radio-frequency performance measures and other diagnostic data for the detection network over a user defined period.
- *Statistics* (WR_VOLUME_30S/ WR_VOLUME_5min) - traffic statistics from all sensor zones at fixed intervals. Counts, occupancy are available for each sensor zone. The speed information is not available currently.
- *Raw event* (WR_VOLUME_RAW) - individual, per-vehicle detections from sensor pairs at the time of the detection event.
- *Travel time* (WR_TRAVEL_TIME) - segment travel time collected from a pair of travel time sensor zones.

Table 11 provides the name, data type, and definition of each column in each table.

Table 11. Columns in the Tables of Dynamic Sensor Information

WR_SENSOR_DIAGNOSTICS		
sensor_diagnostics_id	int	ID of the sensor diagnostics record
time_stamp	double	start time of diagnostic report, in Unix Epoch seconds
period	double	report period in seconds, i.e. 30 for this table
sensor	varchar(20)	name of the sensor for diagnostic
access_point	varchar(20)	access point of the sensor
status	int	sensor status, 1 for "OK" and 0 for "not OK"
WR_VOLUME_30S		
volume_30s_id	int	ID of the 30-seconds statistics record
time_stamp	double	start time of statistics report, in Unix Epoch seconds
period	double	report period in seconds, i.e. 30 for this table
sensor_zone	varchar(20)	name of the sensor zone for statistics
volume	int	traffic volume, in veh
occupancy	double	occupancy, in %, range: 0-100
speed	double	speed, -1 if not available
WR_VOLUME_5MIN		
volume_5min_id	int	ID of the 5-minutes statistics record
time_stamp	double	start time of statistics report, in Unix Epoch seconds
period	double	report period in seconds, i.e. 300 for this table
sensor_zone	varchar(20)	name of the sensor zone for statistics
volume	int	traffic volume, in veh
occupancy	double	occupancy, in %, range: 0-100
speed	double	speed, -1 if not available
WR_VOLUME_RAW		
volume_raw_id	int	ID of the raw event record
time_stamp	double	time of the event, in Unix Epoch seconds
sensor	varchar(20)	name of the sensor for raw event
sensor_long	varchar(20)	long name of the sensor for raw event
access_point	varchar(20)	access point of the sensor
event	int	event id, range: 0-5
WR_TRAVEL_TIME		
travel_time_id	int	ID of the travel time record
time_stamp	double	time of that the vehicle passes the downstream sensor
segment	int	ID of the travel time segment, range: 35-51
travel_time	double	segment travel time of the vehicle

4.4 Signal Information

Signal information includes all signal-related tables (Table 12). The WR_CONTROLLER and WR_PHASE tables list the controller names and phase id used in the signal control system. The WR_SIGNAL_STATIC table assigns a phase to each lane group at each intersection, which associates the signal controllers and geographic information. The WR_SIGNAL_DYNAMICS table provides the phase-by-phase record from the controller.

Table 12. Columns in the Tables of Signal Information

Currently, the signal timing data from the Wolf Road field server must be manually once a day or once a week, and then the data is post-processed and saved into the database.

WR_CONTROLLER		
controller	varchar(20)	controller id, former controller are 4-digit numbered; ACS Lite controllers are numbered from 1-8
controller_type	varchar(20)	type of controller, including: former, ACS Lite
WR_PHASE		
phase_id	varchar(20)	ID of the phase, range: 1-8
WR_SIGNAL_STATIC		
signal_static_id	int	ID of the static signal record
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the signal phase
lane_group	varchar(10)	lane_group of the signal phase
controller	varchar(20)	controller id
phase_id	varchar(20)	ID of the phase, range: 1-8
WR_SIGNAL_DYNAMICS		
signal_dynamics_id	int	ID of the dynamic signal information record
cycle_start	double	start time of the cycle, in Unix Epoch seconds
controller	varchar(20)	controller id
phase_id	varchar(20)	ID of the phase, range: 1-8
cycle length	double	cycle length in seconds
phase_start	double	start time of the phase , in Unix Epoch seconds
phase_duration	double	phase duration in seconds

4.5 Signal Performance

The signal performance tables record the average delay and Level of Service (LOS) of all movements at all intersections for certain time periods (Table 13). The delay calculation method in HCM2010 (2000) is applied.

Table 13. Columns in the Tables of Signal Performance

WR_PERFORMANCE_5MIN		
performance_5min_id	int	ID of the 5 minute performance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement
WR_PERFORMANCE_HOURLY		
performance_hourly_id	int	ID of the hourly performance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement
WR_PERFORMANCE_DAILY		
performance_DAILY_id	int	ID of the daily performance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement

Table 13 continued

WR_PERFORMANCE_WEEKLY		
performance_weekly_id	int	ID of the weekly performance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement
WR_PERFORMANCE_MONTHLY		
performance_monthly_id	int	ID of the monthlyperformance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement
WR_PERFORMANCE_ANNUAL		
performance_annual_id	int	ID of the annual performance record
time_stamp	double	start time of performance report, , in Unix Epoch seconds
intersection_id	int	intersection ID of the signal
approach	varchar(10)	approach of the study movement, "All" for the intersection performance
movement	varchar(10)	study movement, "All" for the approach performance
delay	double	delay of the traffic for the movement
level_of_service	varchar(10)	LOS of the movement

4.6 511NY Event

The traffic events data are acquired from the 511NY XML data feeds (Table 15). The definition of all variables in the table can be found in New York State Department of Transportation 511NY XML Data Feed API Documentation (https://511ny.org/developers/resources).

Table 14. Columns in the Tables of Event Data

WR_EVENT_511NY		
last_update	bigint	time the event was last updated (in in Unix Epoch).
event_type	varchar(50)	Specific event type description.
facility_name	varchar(100)	Name of the facility affected by the event.
direction	varchar(20)	Direction of traffic flow affected by the event.
from_loc_point	varchar(100)	Starting location of the event.
event_id	varchar(20)	Unique ID of the event (19 character string).
event_state	varchar(20)	Whether the event is in the opened or updated state.
event_class	varchar(50)	Incident/Transit Incident/Active Construction/Transit Active Construction/Construction/Transit Construction/Special Event/Active Highway Special Event/Active Special Event/Transit Special Event/Transit Active Special Event
report_org_id	varchar(50)	Organization responsible for reporting the event.
article_code	varchar(20)	Descriptor corresponding to the from and to location. (ex. on, at, between)
to_loc_point	varchar(100)	Ending location of the event.
create_time	bigint	Time the event was created.
event_description	varchar(1000)	Full event description containing detailed event information.
city	varchar(50)	City location of the event.
county	varchar(50)	County location of the event.
state	varchar(20)	State location of the event.
est_duration	bigint	Number in seconds that the event is expected to be active for.
lat	double	Starting latitude location of the event (signed floating point number).
lon	double	Starting longitude location of the event (signed floating point number).
to_lat	double	Ending latitude location of the event (signed floating point number).
to_lon	double	Ending longitude location of the event (signed floating point number).

Table 14 continued

WR_EVENT_511NY		
lanes_affected	bigint	Number of lanes affected by the event.
lane_status	varchar(50)	Lane status descriptor (ex. closed, blocked).
total_lanes	bigint	Total number of lanes affected by the event.
lane_description	varchar(50)	Lane descriptor (ex. 1 lane may be, right lane and shoulder, left and center lanes).
lane_detail	varchar(50)	Detailed lane description (ex. local lanes, local and express roadways, express lanes).
update_number	bigint	Number of times the event has been updated.
respond_org_id	varchar(50)	Organization or application responsible for the event entry.
pavement_condition	varchar(100)	Condition of pavement where the event is located.
weather_condition	varchar(100)	Weather condition where the event is located.
start_date	bigint	Time the event is scheduled to begin.
end_date	bigint	Time the event is scheduled to close.
event_other_desc	varchar(500)	Other descriptive information about the event (ex. 15 minute delays, 2 mile delay).
from_mile_marker	double	Starting milemarker affected by the event on the facility affected by the event.
to_mile_marker	double	Ending milemarker affected by the event on the facility affected by the event.
local_only	bigint	Indicates whether the event is local to a particular agency, or is seen agency-wide (always false).
construction_type	varchar(100)	(ex. C,E,M,O,P)
confirmation_code	varchar(100)	Agency defined code usually associated with construction events. Not always used and not typically needed for public consumption.
closure_type	bigint	Indicates the type of event closure. For internal use only.

4.7 Java Programs for Wolf Road

The team developed various Java programs for data collection from NYSDOT, Sensys Networks and 511NY, delay calculations, and related purposes. Table 15 lists all the Java programs that have been developed by the team with major input files and output tables in the database.

Table 15. Java Programs

Program	Input	Output
ReadRaw	Sensys raw event xml	WR_VOLUME_RAW
ReadStats	Sensys statistic xml	WR_VOLUME_30S, WR_VOLUME_5MIN
ReadDiag	Sensys diagnostics xml	WR_DIAGNOSTICS
ReadTime	Sensys travel time xml	WR_TRAVEL_TIME
ReadSignalSheet	DOT split sheet	WR_SIGNAL_DYNAMIC
ReadACSLite	ACSLite phase time data	WR_SIGNAL_DYNAMIC
DelayHCM	WR_VOLUME_30S, WR_SIGNAL_DYNAMIC	WR_PERFORMANCE_5MIN, WR_PERFORMANCE_HOURLY, WR_PERFORMANCE_DAILY, WR_PERFORMANCE_WEEKLY, WR_PERFORMANCE_ANNUAL
Read511NY	511NY xml feed	WR_EVENT_511NY

5 Development of Quantitative Analysis Tool

5.1 Data Description

This chapter describes how the quantitative decision-making tool was developed. It starts with the data that have been used for the development. The data were archived in the Wolf Road database as discussed in Chapter 4. In particular, the signal performance table, the traffic events table, and the weather table were used. The signal performance table is composed of average delay, level of service (LOS), volume, ratio of volume and capacity (vcr), event and weather of all movements at all intersections for certain time periods. The delay calculation method in HCM (2010) was applied. The traffic events data are binary variables. The event column takes “1” if an incident, construction, or special event occurred on Wolf Road for certain time period. The weather data were recorded as rainfall (inches) or snowfall (inches). The data were archived every five minutes from February to April and August to October in 2013, which was the separated time period for the actuated traffic and adaptive traffic control systems, respectively. Table 16 provides a snapshot of the signal performance table in the database.

Table 16. Signal Performance Table

time_stamp	intersection_id	approach	movement	delay	volume	vcr	occupancy	level_of_service	LOS	Event	Weathe
1359694800	1	SB	All	16.95024539	44	0.002516721	1.315625	B	1	0	0
1359694800	2	EB	All	22.09850607	183.48	0.066205552	1.101	C	1	0	0
1359694800	2	NB	All	8.36556264	136	0.006983499	2.640291667	A	1	0	0
1359694800	2	WB	All	14.96608115	116	0.033019979	1.543291667	B	1	0	0
1359694800	4	NB	All	0.309200989	96	0.004929529	2.640291667	A	1	0	0
1359694800	4	SB	All	0.304059804	48	0.002745514	1.315625	A	1	0	0
1359694800	4	WB	All	45.02334584	8	0.00227724	1.543291667	D	-1	0	0
1359694800	5	NB	All	0.001337493	104	0.005340323	2.640291667	A	1	0	0
1359694800	5	SB	All	0.113727514	72	0.004118271	1.315625	A	1	0	0
1359694800	6	EB	All	32.70788445	20	0.007216651	1.101	C	1	0	0
1359694800	6	NB	All	8.160981256	92	0.004724131	2.640291667	A	1	0	0
1359694800	6	SB	All	1.935418831	72	0.004118271	1.315625	A	1	0	0
1359694800	6	WB	All	10.99996897	16	0.00455448	1.543291667	B	1	0	0
1359694800	7	NB	All	0.165280922	72	0.003697146	2.640291667	A	1	0	0
1359694800	7	SB	All	0.167075232	100	0.005719821	1.315625	A	1	0	0
1359694800	7	WB	All	91.35016872	8	0.00227724	1.543291667	F	-1	0	0
1359694800	8	NB	All	0.534684274	76	0.003902543	2.640291667	A	1	0	0
1359694800	8	SB	All	0.533279134	68	0.003889478	1.315625	A	1	0	0
1359694800	8	WB	All	68.75104274	12	0.00341586	1.543291667	E	-1	0	0
1359695700	1	SB	All	17.41932161	44	0.002566241	1.755958333	B	1	0	0
1359695700	2	EB	All	25.5587206	299.74	0.086933721	0.6495	C	1	0	0
1359695700	2	NB	All	7.252338553	90	0.004640419	2.034791667	A	1	0	0
1359695700	2	WB	All	18.69338778	32	0.008022917	1.280416667	B	1	0	0
1359695700	4	NB	All	0.461493032	76	0.003918576	2.034791667	A	1	0	0
1359695700	4	SB	All	0.454173282	28	0.001633063	1.755958333	A	1	0	0
1359695700	4	WB	All	45.02334584	8	0.002005729	1.280416667	D	-1	0	0
1359695700	5	EB	All	46.84259906	24	0.00696073	0.6495	D	-1	0	0.35
1359695700	5	NB	All	0.452555405	68	0.003506094	2.034791667	A	1	0	0.35
1359695700	5	SB	All	0.448951512	44	0.002566241	1.755958333	A	1	0	0.35
1359695700	5	WB	All	46.16559226	4	0.001002865	1.280416667	D	-1	0	0.35
1359695700	6	EB	All	33.79065482	16	0.004640487	0.6495	C	1	0	0.35

Table 17a shows the overall network performance on Wolf Road for all movements for two time periods: February to April and August to October in 2013, representing the “before” (actuated signal control) and “after” (adaptive signal control) scenarios, respectively. By comparing the percentage of each level of service, it is observed that adaptive signal produces more LOS D, E, F. Table 17b and Table 17c illustrate that, after the deployment of the adaptive control, the LOS on for both the major street and the minor street got degraded, while the LOS for the minor street got even worse.

The aim of this report was to apply big data analysis methods to further analyze the data to gain deeper insight on under what conditions adaptive control is more (or less) suitable for deploying adaptive control. Note that the big data method can be better developed if data from more corridors can be collected and used. The size of the data from only the Wolf Road corridor is not huge (about 40 GB or so) and arguably not big data. However, the Wolf Road dataset already contains various data elements from different sources, dynamic (such as volume data coming in every 30 seconds), and contains errors and data gaps due to detection or communication issues. In this sense, the data perfectly satisfies the Variety, Velocity, and Veracity characteristics of big data.

Table 17. Network Performance

(a) Network performance for all movements

	Feb-April, 2013	Aug-Oct, 2013
Total record	194,215	176,468
LOS A %	36.39%	34.72%
LOS B %	26.41%	13.32%
LOS C %	20.96%	21.78%
LOS D %	11.05%	15.62%
LOS E %	3.76%	8.74%
LOS F %	1.43%	5.83%

(b) Network performance for SB and NB (Major Street)

	Feb-April, 2013	Aug-Oct, 2013
Total record	97,117	88,281
LOS A %	69.62%	64.84%
LOS B %	18.03%	17.75%
LOS C %	11.29%	8.69%
LOS D %	0.98%	7.82%
LOS E %	0.06%	0.57%
LOS F %	0.02%	0.33%

(c) Network performance for WB and EB (Minor Street)

	Feb-April, 2013	Aug-Oct, 2013
Total record	97,098	88,187
LOS A %	3.15%	4.57%
LOS B %	34.80%	8.88%
LOS C %	30.64%	34.89%
LOS D %	21.12%	23.42%
LOS E %	7.46%	16.92%
LOS F %	2.84%	11.33%

The team applied numerous data analytics methods to analyze the Wolf Road data and develop a "knowledge base," including various regression analysis methods and support vector machines (SVM). The following sections will describe each analysis method in detail.

5.2 Regression Method

5.2.1 Multiple Linear Regression

In multiple linear regressions (MLR), a number of variables can be involved and regressed on one another as in Equation 1:

Equation 1. $\boldsymbol{Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n}$

The relationship between two or more explanatory variables and response variables can be modeled by a linear equation.

The MLR was performed using delay as dependent variable and the others (volume, vcr, and occupancy) as independent variables. The estimated models were shown as Equation 2 and Equation 3 for actuated signal data and adaptive signal data.

Equation 2. $\boldsymbol{Delay1 = 20.30 + 0.18 * Volume - 46.37 * vcr - 1.47 * Occupancy}$

Equation 3. $\boldsymbol{Delay2 = 18.80 + 0.02 * Volume + 68.65 * vcr + 0.33 * Occupancy}$

Given the values of all independent variables in Table 18, the delay can be predicted based the models below. The delays are estimated as 38 seconds under adaptive signal and 18 seconds under actuated signal.

Table 18. Examples of Multiple Linear Regression Model

volume	vc ratio	occupancy	Delay1	Delay2
200	0.1	25	18	38

The R-squared value for actuated signal data was improved to 0.48 while there is no major improvement for adaptive signal data (Table 19c and Table 19d). More regression models should be investigated to fit the data.

Table 19. Parameter Estimation and R-squared Value for Multiple Linear Regression

a) Parameter estimation for actuated signal data

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	20.30133	1.20252	16.88	<.0001
VOLUME	1	0.18480	0.02088	8.85	<.0001
VCR	1	-46.71703	158.82227	-0.29	0.7687
OCCUPANCY	1	-1.46526	0.12332	-11.88	<.0001

b) Parameter estimation for adaptive signal data

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	18.80827	1.28909	14.59	<.0001
VOLUME	1	0.02022	0.02023	1.00	0.3179
VCR	1	68.65464	89.18294	0.77	0.4416
OCCUPANCY	1	0.33748	0.14977	2.25	0.0245

c) R-squared value for actuated signal data

Root MSE	20.52907	R-Square	0.4788
Dependent Mean	36.29482	Adj R-Sq	0.4775
Coeff Var	56.56198		

d) R-squared value for adaptive signal data

Root MSE	22.71639	R-Square	0.1103
Dependent Mean	30.01595	Adj R-Sq	0.1077
Coeff Var	75.68105		

5.2.2 Polynomial Regression

Polynomial regression is a statistical modeling technique to fit the curvilinear data that either shows a maximum or minimum in the curve. The polynomial regressions are multiple regressions that use power terms of the independent variables as shown in Equation 4.

Equation 4. $$Y = \beta_0 + \beta_1 x + \beta_2 x^2 \ldots + \beta_n x^n$$

In this study, the dependent variable was delay and independent variables were volume, vcr and occupancy. When fitting polynomial regression models, if a particular model term is significant, all terms of lower order should be assumed significant and retained in the regression model. The models produced by polynomial regression were shown in Equation 5 and Equation 6 for actuated signal data and adaptive signal data, respectively.

Equation 5. $$\boldsymbol{Delay1 = 29.52 - 0.58 * Vol + 0.0015 * Vol^2 + 4.18 * Occu - 0.05 * Occu^2 - 1379.79 * vcr + 22989.54 * vcr^2 - 165587.16 * vcr^3}$$

Equation 6. $$\boldsymbol{Delay2 = 26.07 - 0.27 * Vol + 0.0013 * Vol^2 - 5.57 * Occu + 0.56 * Occu^2 - 0.01 * Occu^3 + 1606.62 * vcr - 36421 * vcr^2 + 218891.72 * vcr^3}$$

Table 20c and Table 20d illustrate that R-squared values for actuated and adaptive signal data are both improved in polynomial regression model. Polynomial regression is a more accurate model to fit the data (Table 20).

Table 20. Parameter Estimation for Polynomial Regression Model

a) Parameter estimation for actuated signal data

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	29.5167	0.96080	30.72	<.0001
VOLUME	-0.5842	0.06755	-8.65	<.0001
VOLUME*VOLUME	0.0015	0.00012	12.13	<.0001
VOLUME*VOLUME*VOLUME	-0.0000	0.00000	-11.61	<.0001
OCCUPANCY	4.1809	0.43146	9.69	<.0001
OCCUPANCY*OCCUPANCY	-0.0495	0.00766	-6.46	<.0001
VCR	-1379.7906	496.40485	-2.78	0.0056
VCR*VCR	22989.5354	5804.85577	3.96	<.0001
VCR*VCR*VCR	-165587.1586	14432.01506	-11.47	<.0001

b) parameter estimation for adaptive signal data

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	26.0692	1.62928	16.00	<.0001
VOLUME	-0.2652	0.11170	-2.37	0.0178
VOLUME*VOLUME	0.0013	0.00033	4.07	<.0001
VOLUME*VOLUME*VOLUME	-0.0000	0.00000	-5.40	<.0001
OCCUPANCY	-5.5665	1.13603	-4.90	<.0001
OCCUPANCY*OCCUPANCY	0.5573	0.08155	6.83	<.0001
OCCUPA*OCCUPA*OCCUPA	-0.0133	0.00180	-7.41	<.0001
VCR	1606.6214	534.37034	3.01	0.0027
VCR*VCR	-36421.9801	7611.41386	-4.79	<.0001
VCR*VCR*VCR	218891.7246	33723.75586	6.49	<.0001

Table 20 continued

c) R-squared value for actuated signal data

R-Square	Coeff Var	Root MSE	DELAY Mean
0.690024	80.77705	19.36199	23.96966

d) R-squared value for adaptive signal data

R-Square	Coeff Var	Root MSE	DELAY Mean
0.224228	70.88485	21.27676	30.01595

5.2.3 Logistic Regression

Logistic regression is a type of predictive model that can be used when the dependent variable is a categorical variable with two categories. Thus the dependent variable can take the value 1 with a probability of success (p) or the value 0 with a probability of failure (1-p). In this study, success indicates that the certain signal control system produce LOS A, B, or C under certain conditions while failure refers to LOS D, E, or F. Logistic regression is adopted for the purposes of predicting the LOS given the independent variables.

The independent or predictor variable can take any form (continuous, dichotomous, and/or dummy variable with more than two categories). That is, logistic regression makes no assumption about the distribution of the independent variables. The relationship between the independent and dependent variables is not a linear function as shown in Equation 7:

Equation 7. $$p = \frac{e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_n x_n)}}{1+e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_n x_n)}}$$

where:

- α = the constant of the equation
- β_i= the coefficient of the independent variables.

The computed value, p, is a probability in the range of 0 to 1. The independent variables are volume, vcr, and occupancy.

The important tests generated by logistic regression are the “Tests of Global Null Hypothesis: Beta=0” and the “Analysis of Maximum Likelihood Estimates.” The “Tests of Global Null Hypothesis” are essentially tests of model significance. Typically, the best test to use is the likelihood ratio test, which uses a chi-square test of significance to test whether the slope parameter β_i are significant different from zero. The "Analysis of Maximum Likelihood Estimates" uses Wald statistics to test the null hypothesis H0 that the associated parameter estimates are not equal to zero.

Logistic regression model is appropriate for experimental data based on the likelihood ratio test. The parameters corresponding to each independent variable are significant. Table 21a and Table 21c show the statistic results for actuated signal data. The model was estimated as Equation 8.

Table 21. Tests in logistic regression

a) Test of model significance for actuated signal data

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	124.7228	3	<.0001

b) Test of model significance for adaptive signal data

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	82.6464	3	<.0001

c) Parameters estimation for actuated signal data

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.2660	0.0998	7.1026	0.0077
VOLUME	1	-0.0448	0.00579	59.8060	<.0001
VCR	1	272.8	34.2626	63.3968	<.0001
OCCUPANCY	1	-0.0512	0.0152	11.2921	0.0008

d) Parameters estimation for adaptive signal data

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	1.0433	0.1260	68.6030	<.0001
VOLUME	1	0.00171	0.00140	1.4795	0.2239
VCR	1	-11.8478	6.7919	3.0429	0.0811
OCCUPANCY	1	-0.0551	0.0144	14.6141	0.0001

$$\textbf{Equation 8.} \quad P_1(LOS = ABC) = \frac{e^{0.27-0.05*Volume+272.8*vcr+0.05*occupancy}}{1+e^{0.27-0.05*Volume+272.8*vcr+0.05*occupancy}}$$

Table 21b and Table 21d show the statistic results for adaptive signal data. The model and parameters are significant. The model was estimated as Equation 9.

$$\textbf{Equation 9.} \quad P_2(LOS = ABC) = \frac{e^{1.04+0.0017*Volume-11.84*vcr-0.06*occupancy}}{1+e^{1.04+0.0017*Volume-11.84*vcr-0.06*occupancy}}$$

Table 22 illustrates how to use logistic regression model. Given the value of volume, vcr, and occupancy, the predicted percentage that actuated and adaptive signal control system will produce LOS A, B, or C are estimated as 91.91% and 41.56%, respectively.

Table 22. Example of logistic regression

volume	vc ratio	occupancy	P1	P2
200	0.1	25	91.91%	41.56%

It turns out that regression analysis methods, including linear regression, polynomial regression, and logistic regression, do not work very well for the purpose of this study. The low R values in linear and polynomial regression indicate that the models do not fit the data well. The available variables are rather limited, which cannot capture the characteristics of delay. Moreover, multicollinearity exists in the predicted model in which two or more predictor variables in the regression model are highly correlated, such as volume and vcr. A more advanced method is applied later in order to study the pattern of the data.

5.3 Support Vector Machine (SVM) Method

This section focuses on applying the robust pattern classification method called SVM (Corinna and Vladdimir, 1995). In the SVM method, features are extracted from the data sets to characterize the “good” (LOS A, B, C) and “bad” (LOS D, E, F) performances. A linear SVM model was applied to distinguish the good and bad performances, and their conditions. Linear SVM is briefly introduced here; references (Biship 2006; Gunn 1998) give more details.

SVM is a method to classify data points into two (or multiple) classes. It defines the criterion to look for a decision hyperplane that is maximally far away from any data point. The decision function for an SVM is specified by a subset of the data, which are referred to as the support vectors. A decision hyperplane can be defined by an intercept term b and a decision hyperplane normal vector $\vec{w}$, which is perpendicular to the hyperplane. All the points $\vec{x}$ on the hyperplane satisfy Equation 10.

Equation 10. $\vec{w}^T\vec{x} + b = 0$

Suppose there are a set of training data points D = $\{(\vec{x}_i, y_i)\}$, where each point is a pair of features $\vec{x}_i$ and a class label y_i. For the two classes separation, y_i is always taking the value +1 or -1. The linear SVM classifier is then defined as Equation 11.

Equation 11. $y_i(\vec{w}^T\vec{x} + b) \geq 1$

In SVM, two major steps are involved: training and testing. The optimal value of $\vec{w}$ and b can be uniquely determined with the training data. The margin is twice the absolute value of the distance between the support vectors to the separating hyperplane. The optimal SVM classifier can be obtained by maximizing the margin.

The distance from the closest sample $\vec{x}_i$ to the optimal hyperplane $g(x) = 0$ is $\frac{|\vec{w}^T\vec{x}_i+b|}{\|w\|} = \frac{1}{\|w\|}$. Thus, the primal problem becomes a quadratic function and there is a single global minimum as shown in Equation 12 and Equation 13.

Equation 12. **Maximize margin:** $m = \frac{2}{\|w\|}$

Equation 13. **s.t.** $y_i(\vec{w}^T\vec{x}_i + b) \geq 1$

The solution involves constructing a dual problem using the Kuhn-Tucker theorem, where a Lagrange multiplier α_i is associated with each constraint in the primal problem (Equation 14 and Equation 15).

Equation 14. **Max:** $\sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j \vec{x}^T{}_i\vec{x}_j$

Equation 15. **s.t.** $a_i > 0 \; \forall \; i$ **and** $\sum_{i=1}^{n} a_i y_i = 0$

The solution is then of the form of Equation 16 and Equation 17.

Equation 16. $\vec{w} = \sum \alpha_i \, y_i \vec{x}_i$

Equation 17. $b = y_k - \vec{w}^T\vec{x}_k$ **for any** $\vec{x}_k$ **such that** $\alpha_k \neq 0$

Each nonzero α_i indicates that the corresponding $\vec{x}_i$ is a support vector.

The classification function is then shown as Equation 18.

Equation 18. $g(\vec{x}) = sign(\sum a_i y_i \, \vec{x}^T{}_i\vec{x} + b)$

In summary, the training data set uniquely defined the optimal separating hyperplane. The quadratic optimization problem is solved to find the plane. The classification function from Equation 18 is computing the projection of the point onto the hyperplane. The sign of this function indicates the class that the point belongs to. This SVM is for classes that are perfectly separable. For practical applications, classes may have overlaps and cannot be perfectly separable. In this case, an error term can be introduced as the tolerance for overlapping. This error term is then added to the objective to be minimized. More details related to transportation applications are in Biship (2006), Sun and Ban (2013), and Yang et al. (2015).

5.4 Development of the SVM-Based Quantitative Analysis Tool

The quantitative decision-making tool is based on SVM and the data collected from the Wolf Road Corridor. Through analyzing the data, certain patterns are expected, based on which to develop an easy-to-use procedure to determine whether adaptive control should be deployed for a specific location. Two ways were proposed to develop such procedures, based on how the actual before and after comparisons are conducted.

5.4.1 Linear SVM for Before and After Classification

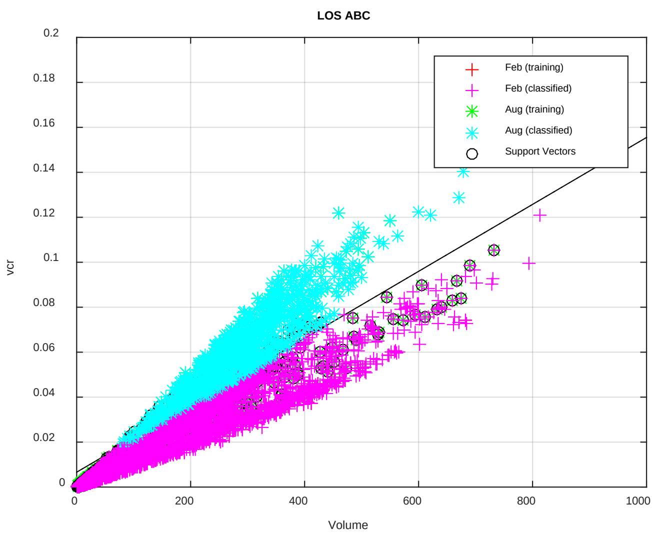
In this section, two separate data sets were used to compare the different patterns. Data set LOS ABC includes all the data that contribute to “good” network performance. Dataset LOS DEF contains all the data points that produce “bad” performance. SVMs are then applied to each of the two data sets to distinguish between the actuated signal control (before) and the adaptive control (after). Because the SVM distinguished before and after performances (for both LOS A-C and LOS D-F), it is called “BC-based” SVM procedure in this report.

It is usually observed that larger traffic volume could lead to longer delay and worse network performance. Also, vcr indicates the level of traffic congestion. These two variables are the most important features that can be used to separate sample data into two network performance classes. The other features used in SVM include occupancy, event, and weather. Among all sample points that were used in the SVM analysis, 70% of them were used for training which were used to find the optimal separating hyperplane. The others were used for testing, which can be used as the decision-making tool to determine if adaptive control is suitable for a given new corridor.

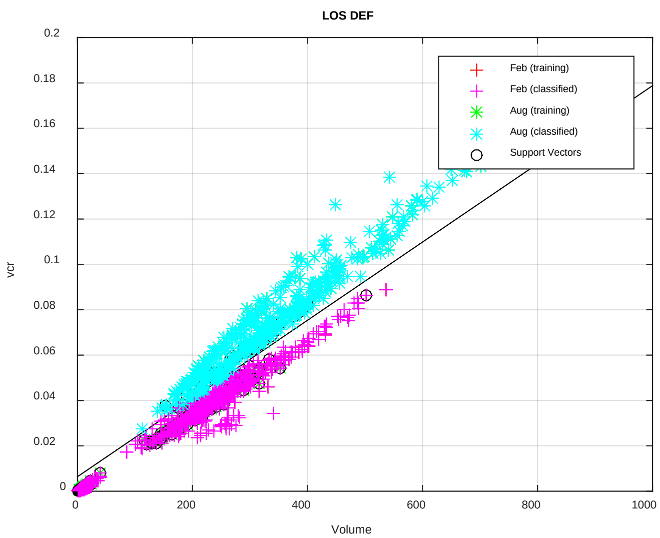
To help explain this concept better, volume and vcr were used to show the SVM results. Figure 11a and Figure 11b show how the separating lines differentiate the data points from adaptive control to actuated control based on the volume and vcr. The discriminant functions for the data sets LOS ABC and LOS DEF are show in Equation 19 and Equation 20.

Figure 11. Two-Feature SVM Results – BC Based

a) SVM model for data set LOS ABC



b) SVM model for data set LOS DEF

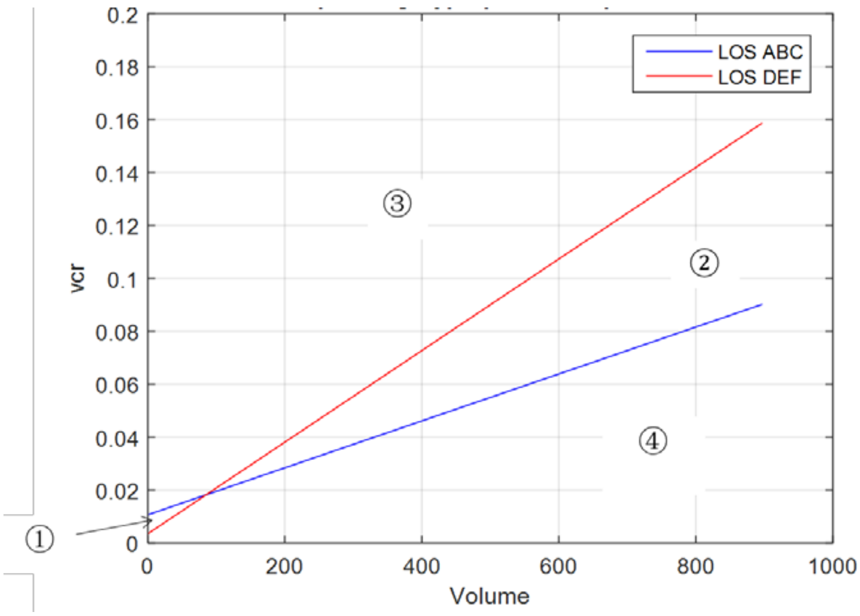


Equation 19. $G_1(x) = 0.009 * Volume - 101.49 * vcr + 2.08$

Equation 20. $G_2(x) = 0.025 * Volume - 144.44 * vcr - 0.04$

By showing the two separating hyperplanes from Figure 11 in Figure 12, the performance of actuated control and adaptive control can be better illustrated based on four different sections in the volume-vcr two-dimensional space. If most of the data occupy section 1 which indicates $G_1(x) < 0$ and $G_2(x) > 0$, actuated control should be recommended because it will produce better level of service (LOS A, B, or C) than adaptive control. Section 2 is directly opposite to section 1 in the sense that adaptive control produces better performance. Section 3 and section 4 are undetermined because the two discriminant functions have the same prediction results.

Figure 12. Separating Hyperplane Comparison – BC Based



Considering all five features in the SVM models, the distinct functions for LOS ABC and LOS DEF are shown in Equation 21 and Equation 22. Given all values for the five features, the SVM model can predict which traffic control system can produce "good" or "bad" level of service based on the sign of $G_1(x)$ or $G_2(x)$. If their signs are both negative and both positive, the two traffic signal control systems have no major difference. The signs of of $G_1(x)$ and $G_2(x)$ actually divide the entire space into four sections. $G_1(x) < 0$ and $G_2(x) > 0$ is defined as section 1, for which actuated control system should be recommended. $G_1(x) > 0$ and $G_2(x) < 0$ is defined as section 2, for which adaptive control system should be recommended.

Here is an example that illustrates how to use the model. If the variables are known as volume = 400, vcr = 0.1, occupancy=30, event=0, weather=3, the values of $G_1(x)$ and $G_2(x)$ can be calculated based on Equation 21 and Equation 22. Because $G_1(x) = -8.71 < 0$ and $G_2(x) = 1.5 > 0$ in this example, actuated control should be recommended according to the SVM model.

Equation 21.

$$\boldsymbol{G_1(x) = 0.02 * Volume - 312.67 * vcr + 0.3 * Occupancy - 9.32 * Event + 1.69 * Weather + 0.42}$$

Equation 22.

$$\boldsymbol{G_2(x) = 0.01 * Volume - 90.89 * vcr + 0.04 * Occupancy - 2.73 * Event + 0.12 * Weather + 2.27}$$

Table 23a and Table 23b show the feature selections and their classification results. Notice that the misclassification rate is defined as the number of falsely classified data points over the total number of data points; false positives is defined as the number of data points under adaptive control misclassified as actuated control; false negative is defined as the number of data points under actuated control misclassified as adaptive control. As the number of features considered by the model increases, all the error rates decrease as shown in Table 23. In particular, if all five features are used, the error rates are about 10% or less, which shows very good classification performance.

Table 23. Feature Selection and Classification Results for LOS

a) Feature selection and classification results for LOS ABC

No.	Features	Number of features	Misclassification rate (testing)	Misclassification rate (training)	False positive (testing)	False negative (testing)	False positive (Training)	False negative (Training)
1	volume/vcr	2	0.234	0.225	0.079	0.155	0.074	0.151
2	vcr/occupancy	2	0.238	0.229	0.100	0.138	0.093	0.136
3	volume/occupancy	2	0.275	0.268	0.097	0.179	0.093	0.175
4	vcr/volume/weather	3	0.145	0.128	0.050	0.095	0.042	0.086
5	vcr/volume/occupancy/weather	4	0.145	0.129	0.052	0.094	0.044	0.085
6	All 5 features	5	0.115	0.102	0.026	0.089	0.020	0.082

b) Feature selection and classification results for LOS DEF

No.	Features	Number of features	Misclassification rate (testing)	Misclassification rate (training)	False positive (testing)	False negative (testing)	False positive (Training)	False negative (Training)
1	volume/vcr	2	0.147	0.135	0.018	0.129	0.014	0.122
2	vcr/occupancy	2	0.246	0.248	0.048	0.197	0.045	0.203
3	volume/occupancy	2	0.247	0.239	0.060	0.187	0.063	0.176
4	vcr/volume/weather	3	0.139	0.131	0.028	0.111	0.024	0.106
5	vcr/volume/weather/event	4	0.082	0.080	0.007	0.075	0.005	0.075
6	All 5 features	5	0.086	0.080	0.007	0.079	0.005	0.075

These SVM results can be used as a decision-making tool for deploying adaptive control at a signalized intersection or a corridor. To use SVM, data related to the previously described features need to be collected for a long period of time (months or years). This amount of collection time will result in a large number of data points. Equation 21 and Equation 22 can then be applied for each data point to check which section it resides. The percentage of the data points can be computed for each section. The decision can then be made on the basis of those percentages, especially the percentages on section 1 and section 2, as previously discussed.

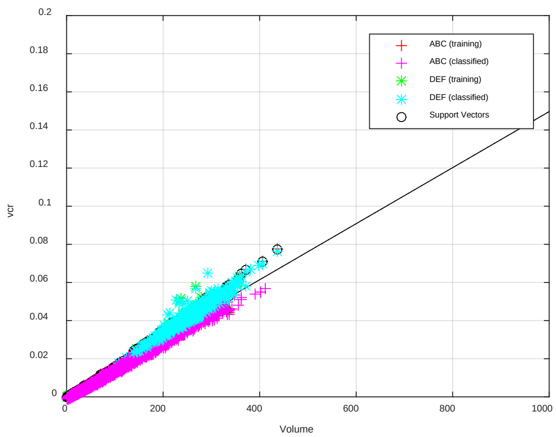
5.4.2 Linear SVM for LOS Classification

This section describes how the features were extracted from data set and used to classify data points into two classes: LOS A, B, or C, and LOS D, E, or F, for both actuated control and adaptive control. It is referred to as “LOS-based” SVM method. The same set of features from the last section is also used here, including volume, vcr, occupancy, weather, and event. SVM models are developed for actuated signal and adaptive signal data separately.

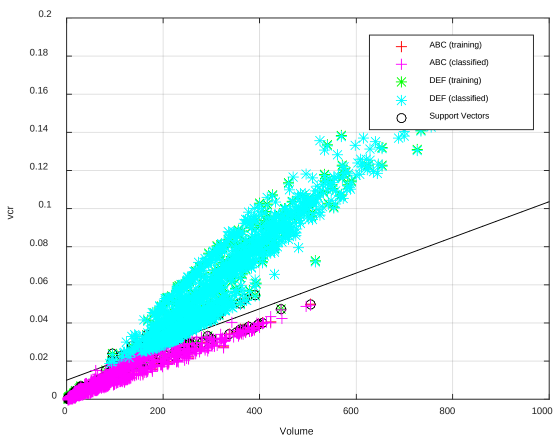
Similar to Figure 11, Figure 13a and Figure 13b show how the separating lines classify the data points from LOS A- C to LOS D- F by considering only volume and vcr. The discriminant functions for the actuated control and adaptive control are given in Equation 23and Equation 24. For a given data point, one can substitute the data point into the two equations. Positive value of $G_1(x)$ or $G_2(x)$ indicates that the data point will lead to worse LOS (LOS D, E, or F) while negative value indicates that the data point will contribute to a better performance (LOS A, B, or C), under their specific traffic control system.

Figure 13. Two-Feature SVM Models – LOS Based

a) SVM model for actuated control using two features (vcr and volume)



b) SVM model for adaptive control using two features (vcr and volume)

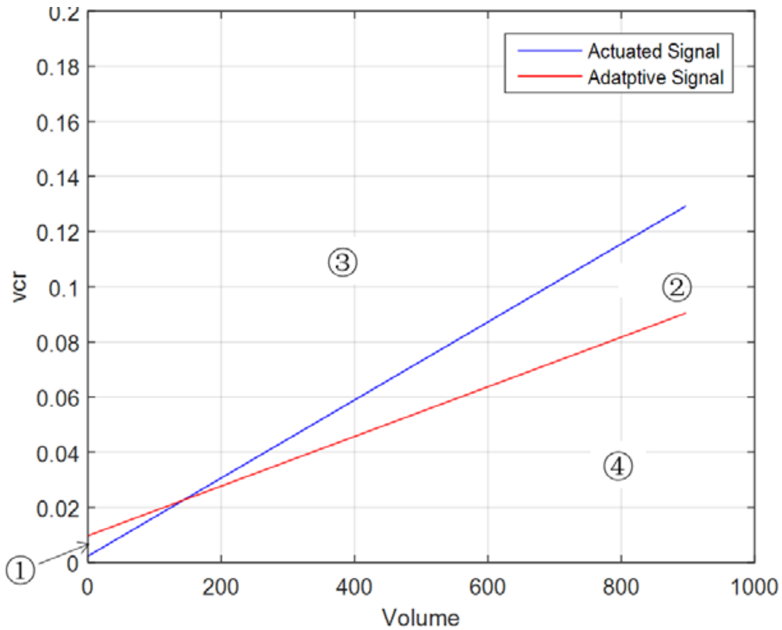


Equation 23. $\boldsymbol{G_1(x) = 0.04 * Volume - 282.69 * vcr + 1.44}$

Equation 24. $\boldsymbol{G_2(x) = 0.01 * Volume - 111.11 * vcr + 1.08}$

The network performance can be compared based on the four sections as shown in Figure 14, which overlays the separating lines from Figure 14. Similar to Figure 12, section 2 represents $G_1(x) > 0$ and $G_2(x) < 0$. If actuated control is installed, the level of service will be D, E, or F because the data point falls into section 2. If adaptive control is deployed, the level of service will be A, B, or C. Therefore, adaptive control is recommended for section 2. On the contrary, section 1 is for $G_1(x) < 0$ and $G_2(x) > 0$, which means actuated control is recommended. Section 3 and section 4 are undetermined.

Figure 14. Separating Hyperplane Comparison – LOS Based



If all five features are used, the distinct function for actuated control and adaptive control are described by Equation 25 and Equation 26, respectively. Because no events occurred before May 2013, the SVM model $G_1(x)$ only contains four features (the feature "event" is not included). If sample data points are available, substituting the values of all features into SVM models, each data point can be mapped into the four sections defined by the sign of $G_1(x)$ and $G_2(x)$. $G_1(x) > 0$ and $G_2(x) < 0$ defines section 2, for which the adaptive control is recommended. $G_1(x) < 0$ and $G_2(x) > 0$ defines section 1, for which the actuated control is recommended. With the same example given before, the values of $G_1(x)$ and $G_2(x)$ are calculated based on Equation 25 and Equation 26. Because $G_1(x) = -74.48 < 0$ and $G_2(x) = 21.4 > 0$, the actuated signal is recommended, which is consistent with the results from before and after analysis.

Equation 25. $\boldsymbol{G_1(x) = -0.17 * Volume + 101.89 * vcr - 0.11 * Occupancy - 0.40 * Weather - 3.37}$

Equation 26.

$$\boldsymbol{G_2(x) = -0.01 * Volume + 206.08 * vcr - 0.16 * Occupancy + 5.02 * Event + 3.46 * Weather - 0.78}$$

Table 24a and Table 24b show the feature selection and classification results from considering different features for the actuated control and adaptive control, respectively. Again the misclassification rate is defined as the number of falsely classified data over total number of data; false positives is defined as the number of data points under LOS ABC misclassified as LOS DEF; false negative is defined as the number of data points under LOS DEF misclassified as LOS ABC. As the number of features considered by the model increases, all the error rates decrease as shown in Table 24. If all five features are used, the error rates are less than 10%. Similar to the BC-based SVM methods, for a given site, one can collect a large amount of data and compute the features. All the data points can be mapped into the four sections as shown above based on $G_1(x)$ and $G_2(x)$. The percentage of data points falling into each section can also be calculated. By comparing those percentages, one can decide whether adaptive control should be deployed of the site.

Table 24. Feature Selection and Classification Results for Actuated and Adaptive Control

a) Feature selection and classification results for actuated control

No.	Features	Number of features	Misclassification rate (testing)	Misclassification rate (training)	False positive (testing)	False negative (testing)	False positive (Training)	False negative (Training)
1	volume/vcr	2	0.220	0.221	0.204	0.015	0.204	0.017
2	vcr/occupancy	2	0.298	0.293	0.261	0.037	0.260	0.033
3	volume/occupancy	2	0.256	0.255	0.213	0.043	0.214	0.042
4	vcr/volume/occupancy	3	0.215	0.202	0.193	0.023	0.189	0.014
5	vcr/volume/occupancy/weather	4	0.026	0.027	0.026	0.000	0.027	0.000

b) Feature selection and classification results for adaptive control

No.	Features	Number of features	Misclassification rate (testing)	Misclassification rate (training)	False positive (testing)	False negative (testing)	False positive (Training)	False negative (Training)
1	volume/vcr	2	0.287	0.307	0.184	0.103	0.205	0.101
4	vcr/volume/occupany	3	0.234	0.220	0.209	0.025	0.202	0.017
5	vcr/volume/occupancy/weather	3	0.232	0.208	0.207	0.025	0.186	0.022
6	vcr/volume/occupancy/event	4	0.098	0.094	0.094	0.004	0.092	0.002
7	vcr/volume/occupancy/event/weather	5	0.096	0.088	0.092	0.004	0.082	0.006

5.5 Quantitative Decision-Making Procedure

To summarize, the following procedure can be used, along with detailed traffic data from a given location, to determine whether adaptive traffic signal control is beneficial if deployed at that location.

SVM-based quantitative decision-making procedure for adaptive control deployment:

1. Collect data (volume, vcr, occupancy, event, weather, etc.), ideally for a few months or even longer.

2. Check the data points against either Method A (Equation 21 and Equation 22) or Method B (Equation 25 and Equation 26) to map the data point into section 1 or section 2 or the other sections. Each data point represents a “vote” for actuated (section 1) control or adaptive (section 2) control.
3. Count the votes. If section 2 gets more votes, adaptive traffic signal control should be recommended. Otherwise, adaptive traffic signal control is not recommended.

5.6 Discussion

Of note, using the two methods for the quantitative analysis may not produce consistent results. Figure 12 and Figure 14 partially illustrate this observation. The two figures indicate that if only vcr and volume are used for decision-making, the two methods may give very different conclusions (Section 2 in Figure 12 is much bigger than Section 2 in Figure 14). Of course, if the five-feature SVMs are used, the differences are expected to be less dramatic. In any case, certain discrepancies in terms of decision-making should be expected by using the two methods. However, it is difficult to tell at this stage which method is better because they are both based on correlations among data samples, rather than investigating the fundamental reasons of why adaptive control is better or not.

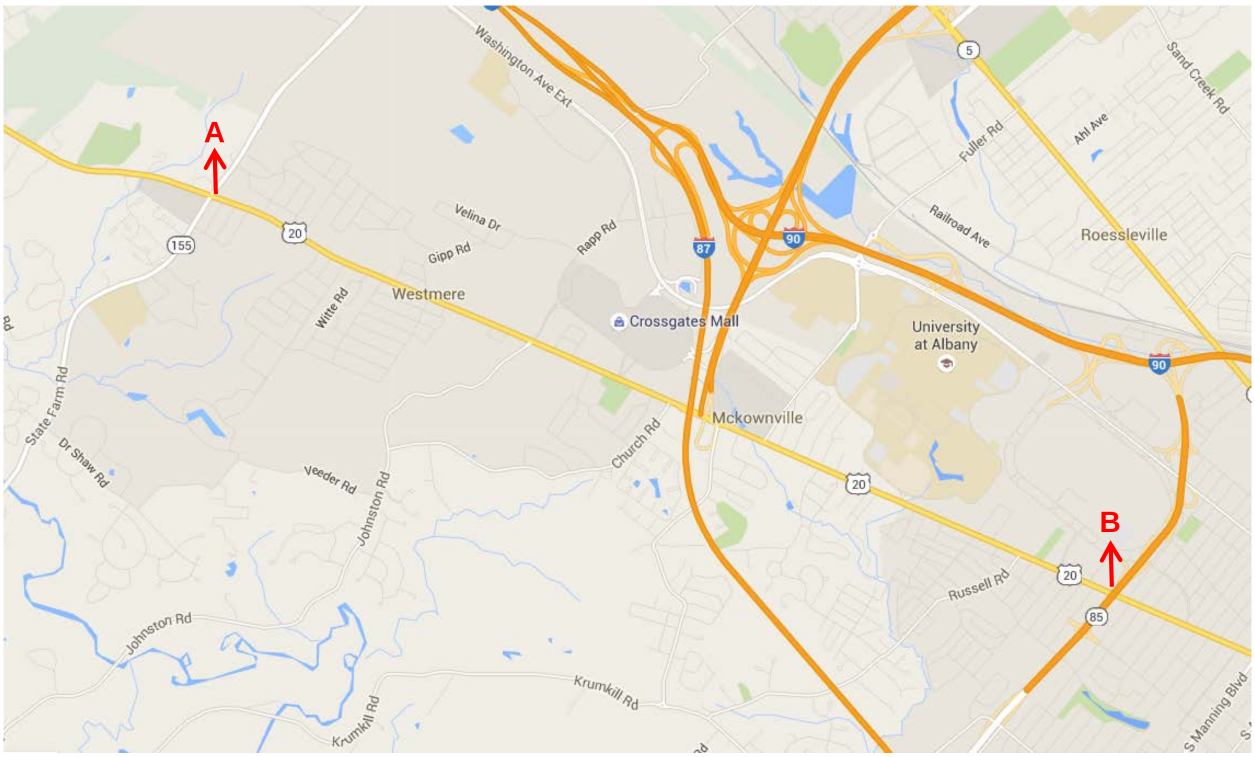
The observation can be attributed to one key feature of big data, which may also be considered as the limitation of big data-based methods. That is, these methods are suitable for decision-making, but not good enough for rigorous scientific investigations, simply because they care only about *what* but not *why*.

There are also potential pitfalls when applying big data analysis methods. As Popper (2014) put it: “everything is similar to everything else in certain respects, and everything is different to everything else in certain respects, so the mere looking for similarities does not take you very far.” At the same time, decision-making or big data method-based predictions assume that the pattern observed in the past will repeat itself in the future. This assumption may not hold true if abrupt events occur. For example, using the airline ticket application from Chapter 1, the big data method may predict that the ticket price will drop in the next couple days and one would be better off to wait to make a purchase. However, a sudden gas price increase may make the price increase significant, thus completely destroying the big data-based prediction. For this and similar reasons, increasing concerns recently in the big data research field call for developing foundational theories to understand what is behind the data correlations (Fricke 2015, Pan et al. 2015). In particular, such theories should be able to help develop engineering methods to control prediction errors from big data methods, in a way similar to engineering procedures to build bridges that were developed based on structural theories.

6 Case Study

The case study in this chapter illustrates how the decision tree in Figure 8 can be used to assess whether adaptive traffic signal control system is suitable for a given corridor. The project team selected the Western Avenue in Albany, NY. It is a 4.5-mile major arterial that connects Interstate 87 and other major roads in the area. Figure 15 shows the boundaries of the study area of Western Ave are Route 155 (point A) and Route 85 (point B).

Figure 15. Route 20 in Albany from Route 155 to Route 85



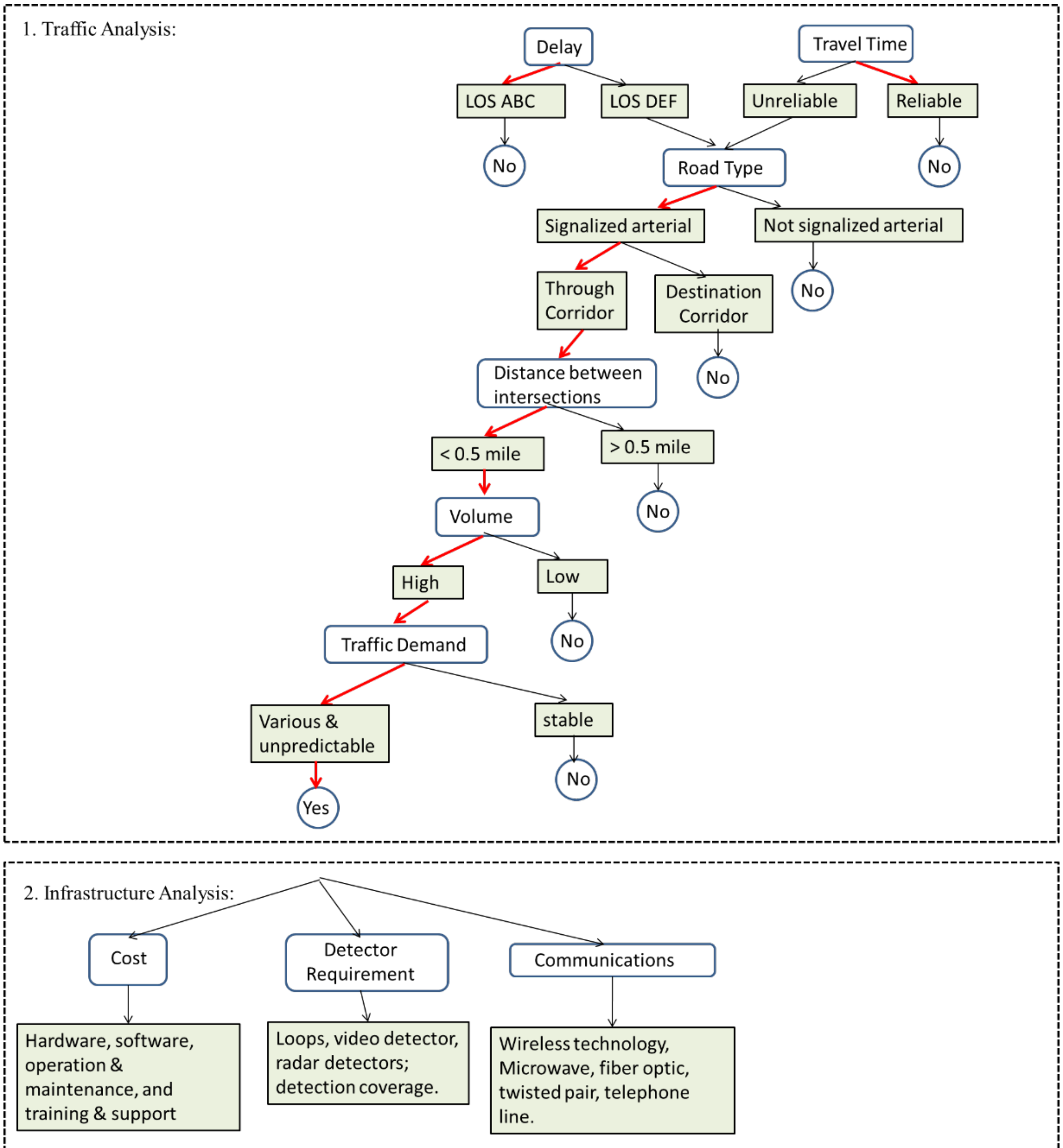
The project team met with NYSDOT staff from Headquarters in Albany and Region 1 to learn about issues of the corridor. The team also did field investigation by driving along the corridor during peak hours. The congestion on the Western Ave is usually at the LOS C level. The travel time is relatively reliable at about 12 min. Table 25 lists the 11 State signals along Western Ave and the distance between them. The length of this corridor is 4.5 mile so the average distance between two intersections is 0.41 mile. Apart from these 11 signals, the City of Albany manages eight additional signals along the corridor. If the City of Albany signals are also integrated with the State signals, the average distance between signals will be much smaller than 0.5 mile (threshold in Decision Tree). The corridor is a through corridor during the peak hour, mainly serving commuting traffic. The volume on Western Ave is high due to the nearby shopping mall, restaurants, and retailers and the commuting traffic during the peak hours. The traffic is usually alleviated during off-peak times, which leads to various and unpredictable traffic demands. As a result, Figure 16 shows the traffic analysis and indicates that adaptive control may not be the best option for Western Ave, mainly due to the current LOS and that the travel time is relatively reliable.

Table 25. Distance between Intersections on Western Ave

Distance indicates between intersections listed next to each other on the list. For example, between Fuller and Parkwood is 0.1 miles.

ID	Intersection	Distance
1	Rte 155	/
2	Witt	0.8
3	Gipp/ Palma	0.3
4	Johnston/ Rapp	0.5
5	Crossgates	0.5
6	Church	0.3
7	Fuller Road Alt / Schoolhouse	0.3
8	Fuller	0.2
9	Parkwood	0.1
10	Norwood/ McKnown	0.1
11	SUNY	0.4

Figure 16. Decision Tree for Western Ave



The Infrastructure Analysis in Figure 16 shows the adequate hardware, software, and communications support needed for operations and to ensure the adaptive signal control algorithms function properly. First, after talking to NYSDOT staff, the local controllers on Western Ave needed to be updated to meet the adaptive traffic control system requirements and be compatible with the central hardware. Training is necessary for field technicians to learn how to use new controllers and other hardware. Second, adaptive signal control systems rely heavily on the traffic data collected from detectors. Inductive loops were installed previously for specific locations of Western Ave, which need to be significantly expanded to serve the needs of adaptive control. For Western Ave, wireless detectors may be installed. Based on the project team's past experience with similar corridors (such as the Wolf Road corridor in Albany), around

200-300 wireless detectors may be needed to upgrade the corridor detection system in order to deploy adaptive control system. Third, communications define the way in which signals are interconnected in adaptive signal control system network, which are a critical component for adaptive control. Communication is not currently available for Western Ave, and must be installed (e.g., fiber cables or Wi-Fi) before deploying the adaptive signal control system. The major upgrades needed for the corridor for installing adaptive control are summarized in Table 26. It is clear from the analysis that the resources needed to deploy such system are quite substantial.

Table 26. Major Upgrades Needed for Western Ave

Hardware	Controller Upgrades
Detection	Wireless detectors installation
Communications	Communication media installation, such as fiber cables or Wi-Fi

From both the traffic and infrastructure analyses for the Western Ave corridor, adaptive traffic signal control may not be the best option for the corridor. Because detailed traffic, weather, and incident related data are not all available for Western Ave, the big data-based, quantitative analysis method proposed in Section 5 cannot be applied to this corridor. In the future, if such data are available, the quantitative method can be applied to the corridor to get more in-depth analysis and results. This quantitative analysis can help conducted more in-depth benefit-cost analysis, which will help document in detail the benefits (in terms of congestion, fuel consumption / emission reductions) and costs (resources) of deploying the adaptive control system. More informed decisions can then be made accordingly.

7 Conclusions

This project developed a qualitative analysis method and a quantitative analysis method to guide traffic engineers and decision-makers deciding about whether adaptive control is best suited for a given traffic corridor and/or intersections. The qualitative analysis method was based on the nation-wide best practice of adaptive traffic signal control deployment. A decision tree was developed to help make decisions based on traffic analysis and infrastructure analysis. The critical factors, such as travel time, delay, volume, LOS, etc. are evaluated in the traffic analysis. Infrastructure analysis discussed the required hardware, software, and cost to deploy adaptive traffic signal control systems.

Development of the quantitative analysis method was based on using a large amount of data from various sources such as wireless detectors and the 511NY system, including volume, occupancy, weather, and special events, among others. Regression models and SVM-based methods were applied to classify the “good” and “bad” performances of signals and to distinguish the adaptive control from the actuated control. The regression models did not work very well for the purpose of this study. Results from the SVM models showed that the misclassification errors decreased as the number of features that the model considered increased. Therefore, the five-feature SVM models should be used. Based on the SVM methods, a quantitative decision-making procedure was then developed to help deploying adaptive traffic signal control systems.

A case study of Western Ave. corridor in Albany, NY demonstrated the qualitative decision-making tool. Due to the lack of detailed data, currently the quantitative analysis tool cannot be applied to the corridor, which is recommended for future studies. The decision tree in Figure 8 and decision-making tool in Section 5.4 may apply to other corridors once sufficient data, such as volume, vcr, occupancy, weather, and event are available.

Major findings and limitations of the proposed decision-making tool and the data analysis methods are summarized as follows:

- Adaptive traffic signal control may not be suitable for any given transportation corridor or intersections. Therefore, careful data collection and analysis should be conducted before deploying adaptive traffic signal control systems. The proposed qualitative analysis and quantitative analysis tools in this project could help conduct high-level and detailed analyses to help make more informed decisions about adaptive signal control system deployment.

- There are various types of adaptive traffic signal control systems. Their performances and costs vary significantly (e.g., past deployment showed the deployment cost varies from $20,000 to nearly $80,000 per intersection). Therefore, careful analysis and selection of the most suitable adaptive traffic signal control system are needed, based on the given specific corridor.
- The quantitative analysis method requires a large amount of data, ranging from traffic-related data, to weather data, to special event data, to make the best use of the big data analysis method. The method should be able to apply to transportation corridors or intersections in other areas. However, the tools presented in this report (such as Figure 12) were developed only based on the data from the Wolf Road corridor. Therefore, the results may not be applicable directly to other corridors. More data from other types of traffic corridors and intersections should be collected to further develop or improve the tool for better decision-making.
- The qualitative and quantitative methods developed in this project should be viewed as technical tools that may facilitate informed decisions about deploying adaptive traffic signal control systems. They should not be viewed as the only tool or criteria for adaptive traffic signal control deployment. Other factors, such as local knowledge and engineering judgement, should also be considered in the decision-making process.

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Albany, NY 12203-6399

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