# AUTOMATIC SIGNAL RETIMING FOR LARGE SCALE NETWORKS WITH VEHICLE TRAJECTORY DATA

Project Number OR24-015: Progress Report


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Submission Date: November 30, 2025

| 1. Report No. | 2. Government Accession No. | 3. MDOT Project Manager |
|---|---|---|
| SPR-1761 | 01957465 | William Seeger |

| | |
|---|---|
| **4. Title and Subtitle**<br>Automatic Signal Retiming for Large Scale Networks with Vehicle Trajectory Data | **5. Report Date**<br>November 30th, 2025<br>**6. Performing Organization Code** |
| **7. Author(s)**<br>Zachary Jerome, Zihao Wang, Xingmin Wang, Henry Liu | **8. Performing Org. Report No.** |
| **9. Performing Organization Name and Address**<br>University of Michigan Department of Civil and Environmental Engineering<br>2350 Hayward Street<br>2105 GG Brown Building<br>Ann Arbor MI 48109-2125 | **10. Work Unit No. (TRAIS)**<br>**11. Contract No.**<br>**11(a). Authorization No.** |
| **12. Sponsoring Agency Name and Address**<br>Michigan Department of Transportation<br>Research Administration<br>425 West Ottawa Street<br>Lansing MI 48933 | **13. Type of Report & Period Covered**<br>Final Report<br>**14. Sponsoring Agency Code** |

**15. Supplementary Notes**

Draft Final Report

**16. Abstract**

This report presents a real-world implementation of a recently developed traffic signal optimization system that uses a small percentage of vehicle trajectory data-also known as probe or telemetry data-as the only input. The system utilizes a new model for designing signal timing plans that leverages the temporal-spatial information of vehicle trajectory data as opposed to traditional software such as Synchro which relies on turning movement counts. This model allows us to accurately reconstruct average recurrent traffic states by aggregating sufficient historical data, even at low penetration rates. In the real-world deployment conducted in coordination with the Michigan Department of Transportation (MDOT) and the Road Commission for Oakland County (RCOC), researchers used vehicle trajectory data from an estimated 7% of vehicles in the traffic network to update cycle lengths, splits, offsets, and timing schedules at seven intersections along a 2.5-mile stretch of a coordinated-actuated arterial in Pontiac, Michigan. This corridor recently went through a traditional signal optimization based on vehicle count data, providing a unique opportunity to directly compare the performance of the new vehicle trajectory-based system against conventional methods. The vehicle trajectory-based system outperformed the traditional approach, reducing the overall control delay by 17.4% and the number of stops by 20.4%, compared to reductions of 13.7% and 14.9%, respectively, achieved by traditional optimization, and a cost analysis demonstrated savings of up to 35%. By utilizing increasingly available vehicle trajectory data as the only input and not requiring any additional infrastructure, we believe our system will provide a more scalable and economical solution to traffic signal optimization that could be applied worldwide.

| 17. Key Words | 18. Distribution Statement |
|---|---|
| Traffic Signal Optimization, Coordinated-Actuated Control, Vehicle Trajectory, Probe Data | No restrictions. This document is available to the public through the Michigan Department of Transportation. |

| 19. Security Classification - report | 20. Security Classification - page | 21. No. of Pages | 22. Price |
|---|---|---|---|
| Unclassified | Unclassified | 31 | $297,999.99 |

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# Contents

# List of Figures

## List of Tables

# Executive Summary

Drivers in the US experience 22.9 billion dollars in congestion costs at intersections controlled by traffic signals each year (*1*). Traffic signal optimization, which adjusts the green time given to each direction according to changing traffic demand patterns, is one of the most cost-effective ways to reduce congestion as it does not require any changes to the physical infrastructure (*2-4*). However, it is very difficult to collect traffic volumes across the more than 330,000 signalized intersections in the country. High installation and maintenance costs often force agencies to utilize temporary detection methods, which can be difficult to manage at large scales. Typically, retiming efforts are conducted on a 3- to 5-year fixed rotation or in response to major land use changes. This timeline is in large part dictated by the need to collect information about the traffic dynamics as part of the project. Improved data sources would also facilitate a transition from infrequent, periodic adjustments to more continuous and responsive optimization as traffic patterns evolve.

In recent years, GNSS data from vehicles equipped with cloud-based or cellular services has become increasingly accessible through crowdsourced applications, including navigation tools and roadside assistance platforms. Vehicle trajectory data—also known as probe or telemetry data—from these vehicles has the potential to bring dynamic and responsive signal control solutions to millions of traffic signals around the world. It provides detailed travel-path information 24/7 across entire traffic networks and, despite limited observations through low penetration rates, can still give insights into the overall traffic performance (*5-8*). A traffic signal retiming system utilizing this data would provide a more feasible and economical solution that could be applied to every traffic signal in the world, providing previously unavailable opportunities to communities without the resources to manage expensive detection systems. However, there are few suitable traffic flow models for this data that allow us to predict traffic states under different traffic signal timing plans.

The purpose of this project is to evaluate the technical readiness for deployment of the University of Michigan's recently developed traffic signal optimization system that uses a small percentage of vehicle trajectory data as the only input. This system utilizes a new model for designing signal timing plans that leverages the temporal-spatial information of vehicle trajectory data as opposed to traditional software such as Synchro which relies on turning movement counts. This model allows us to accurately reconstruct average recurrent traffic states by aggregating sufficient historical data, even at low penetration rates. The system is tested through a real-world deployment conducted in coordination with the Michigan Department of Transportation (MDOT) and the Road Commission for Oakland County (RCOC), where the University of Michigan team used vehicle trajectory data from an estimated 7% of vehicles in the traffic network to update cycle lengths, splits, offsets, and timing schedules at seven intersections along a 2.5-mile stretch of a coordinated-actuated arterial in Pontiac, Michigan. This corridor recently went through a traditional signal optimization based on vehicle count data, providing a unique opportunity to directly compare the performance of the new vehicle trajectory-based system against conventional methods. The vehicle trajectory-based system outperformed the traditional approach, reducing the overall control delay by 17.4% and the number of stops by 20.4%, compared to reductions of 13.7% and 14.9%, respectively, achieved by traditional optimization, and a cost analysis demonstrated savings of up to 35%. By utilizing increasingly available vehicle trajectory data as the only input and not requiring additional infrastructure, we believe our system will provide a more scalable and economical solution to traffic signal optimization that could be applied worldwide.

# Introduction

*Background*

Drivers in the US experience 22.9 billion dollars in congestion costs at intersections controlled by traffic signals each year (*1*). Traffic signal optimization, which adjusts the green time given to each direction according to changing traffic demand patterns, is one of the most cost-effective ways to reduce congestion as it does not require any changes to the physical infrastructure (*2-4*). However, it is very difficult to collect traffic volumes across the more than 330,000 signalized intersections in the country. High installation and maintenance costs often force agencies to utilize temporary detection methods, which can be difficult to manage at large scales. As a result, optimization projects at each intersection are usually only executed every 3-5 years. For MDOT, however, the frequency is closer to every 10 years.

In recent years, GNSS data from vehicles equipped with cloud-based or cellular services has become increasingly accessible through crowdsourced applications, including navigation tools and roadside assistance platforms. Vehicle trajectory data—also known as probe or telemetry data—from these vehicles has the potential to bring more automatic signal control solutions to millions of traffic signals around the world. It provides detailed travel-path information 24/7 across entire traffic networks and, despite limited observations through low penetration rates, can still give insights into the overall traffic performance (*5-8*). A traffic signal retiming system utilizing this data would provide a more feasible and economical solution that could be applied to every traffic signal in the world, providing previously unavailable opportunities to communities without the resources to manage expensive detection systems. As automation and connectivity increase on our traffic networks, there will be greater opportunity for vehicle trajectory-based traffic signal control. However, there are few suitable traffic flow models for this data that allow us to predict traffic states under different traffic signal timing plans.

*Objectives*

The purpose of this project is to evaluate the technical readiness for deployment of the University of Michigan's (UM) recently developed traffic signal optimization system that uses a small percentage of vehicle trajectory data (*9*). This system utilizes the probabilistic time-space (PTS) model, a stochastic traffic flow model that describes the queueing dynamics at the signalized intersection. The model leverages the temporal-spatial information of vehicle trajectory data as opposed to traditional software such as Synchro which relies on turning movement counts. The contributions of this project are twofold. First, whereas the original PTS model was tested in a fixed-time operation setting, this study upgrades the model to accommodate coordinated-actuated operation. UM then conducted a real-world deployment of the upgraded system in coordination with the Michigan Department of Transportation (MDOT) and the Road Commission for Oakland County (RCOC). Using vehicle trajectory data from an estimated 7% of vehicles in the traffic network, the optimization updated cycle lengths, splits, offsets, and timing schedules. Second, the selected study segment recently went through a traditional signal optimization based on vehicle count data, providing a unique opportunity to directly compare the performance of our newly developed vehicle trajectory-based system against conventional methods. Overall, the vehicle trajectory-based system outperformed the traditional approach, reducing the overall control delay by 17.4% and the number of stops by 20.4%, compared to reductions of 13.7% and 14.9%, respectively, achieved by traditional optimization.

*Scope*

This project uses vehicle trajectory data from an OEM provider as the only input to optimize signal timing plans for seven intersections along a 2.5-mile stretch of Telegraph Rd from County Center Dr to Voorheis St in Pontiac, MI. We propose a concise method to improve coordination performance in coordinated-actuated settings by leveraging the temporal-spatial qualities of vehicle trajectory data to estimate the distribution of green start times within the cycle. The green start time probability can then be used as an input in the PTS model. We used this information to model and optimize the signal timing plans by updating the timing plan schedules, offsets, cycle lengths, and green splits. The performance of this implementation was evaluated and compared to a traditional optimization using signal performance measures (SPMs) extracted from the vehicle trajectory data before and after each respective optimization.

*Statement of Hypotheses*

Vehicle trajectory data offers a unique opportunity to enable more systematic, large-scale signal timing management by delivering continuous and widespread insights into current traffic dynamics. However, few comprehensive solutions currently exist that fully leverage the advantages of this data to automatically develop new signal timing plans in response to evolving traffic patterns. Such a solution would offer a more scalable, efficient, iterative, and cost-effective solution that could be applied to signalized intersections around the world.

## Literature Review

*Review of Previous Research*

Increasingly available vehicle trajectory data from various services has bolstered the development of the next generation of traffic signal performance measures that expand upon the existing automated traffic signal performance measures (ATSPMs). Monitoring traffic through vehicle trajectory data is highly scalable due to its large coverage area, offering many advantages over the fixed-point detection methods used for ATSPMs (*5-8*). Common performance measures extracted from each individual trajectory observations are control delay, number of stops, and split failures.

Recent studies have investigated how vehicle trajectory data can be used to optimize traffic signal timing plans in real-world settings. Purdue University worked with the Indiana Department of Transportation (INDOT) to scan their more than 2,000 traffic signals using vehicle trajectory data and prioritize signal retiming activities (*10*). Eleven timing plans were adjusted at nine traffic signals based on identifying "critical movements" and "donor movements" according to split failure ratios, reducing average control delay and split failures by up to 53 seconds and 30\%, respectively. A team from Project Green Light with Google Research used probe data for traffic signal coordination and performed an experimental study in Jakarta, Indonesia, where the average travel time dropped from 14.6 seconds to 9.5 seconds (*11*). In a real-world implementation of the PTS model developed by UM in Birmingham, Michigan, delay and number of stops dropped by up to 20\% and 40\%, respectively, by adjusting offsets on a corridor operated under fixed-time operation (*9*).

This project upgraded previous work of the UM research team by upgrading the PTS model to accommodate coordinated-actuated settings. This type of control maintains coordination by operating actuated control only on the non-coordinated movements since the coordinated major phases must be serviced at the same fixed point in each cycle. In this case, when all the non-coordinated phases gap out, early return to green (ERG) occurs where the coordinated major phase starts earlier than the offset value. It can be difficult to model the variations in ERG start times, which may have a negative impact on the coordination as it can alter the intended green bands (*12*).

Various methods have been proposed to mitigate this issue in vehicle count-based optimization, but they hold a variety of limitations. Some approaches coordinate based on the end of green (*13*), which can compromise efficiency because the densest departures typically occur at the green start, especially under high traffic volumes. Others solely focus on the mean value of the green start (*14*), which does not adequately address extreme scenarios, such as when there is no ERG or ERG occurs very early, both of which are critical to the transportation system. Additionally, some methods encounter implementation challenges due to shortcomings of the algorithm itself, such as stability issues of the algorithm in oscillatory traffic patterns (*15*), or due to reliance on strong assumptions. For instance, arrival patterns or arrival rates of all phases are assumed to be known (*16, 17*). Moreover, other methods rely on archived traffic signal data (*18-20*), which can be difficult to obtain and may vary across different types of controllers.

*Summary of State-of-the-Art*

Traffic signal retiming requires knowledge of current traffic dynamics including traffic volumes, free-flow speeds, and signal performance measures (SPMs) such as delay. The most commonly practiced methods for collecting this information involve fixed-point roadside detections systems such as video cameras and inductive loop detectors, which have high installation and maintenance costs. As a result, a large proportion of the signalized intersections in the United States do not have detection capabilities and are still controlled by fixed-time (pre-timed) traffic signals (*1, 21*). Signal retiming projects at these intersections are usually only executed every 3-5 years in practice (*22*) and rely on temporary detection methods to collect current traffic dynamics. These measurements inform a variety of models that help engineers design new signal timing plans and enable before-and-after performance evaluations of those plans. However, narrow observation windows limit potential traffic signal improvements and evaluation capabilities. Such ``one-shot" optimizations can quickly become outdated as traffic demand undergoes natural changes or growth, which can increase congestion and energy costs. As shown in Figure 1, more responsive signal retiming that decreases the time between each iteration could recover lost opportunities as traffic dynamics change over time (difference between the blue and green shaded areas).

Some intersections with detection capability use vehicle-actuated control, traffic responsive control, or adaptive traffic control systems (ATSC), which are more responsive to the time-varying traffic demand compared to fixed-time traffic signals. While in many cases traffic responsive control and ATSC have proven to be effective, sometimes improving travel times by up to 50% or more, their widespread implementation has been prevented by high installation, maintenance, and software licensing costs (*23*). In addition, actuated signal control has also been discouraged by the National Association of City Transportation Officials (NACTO) because of the maintenance requirements and detection upkeep on streets (*24*). Since a single unreliable detector can jeopardize the effectiveness of an entire ATSC or actuated system, these detectors require frequent monitoring and maintenance. Many agencies have also discovered that ATSC cannot simply be installed and left alone for long periods of time. Some, especially those who are not knowledgeable of the inner workings of ATSC, have been forced to switch back to traditional fixed-timed plans after the original ATSC settings are unable to handle long-term changes in traffic patterns (*25*). As a result, although the first ATSC systems were developed in the early 1970s, only a small percentage of signalized intersections in the U.S. (2-5%) have been outfitted with this technology (*21*).

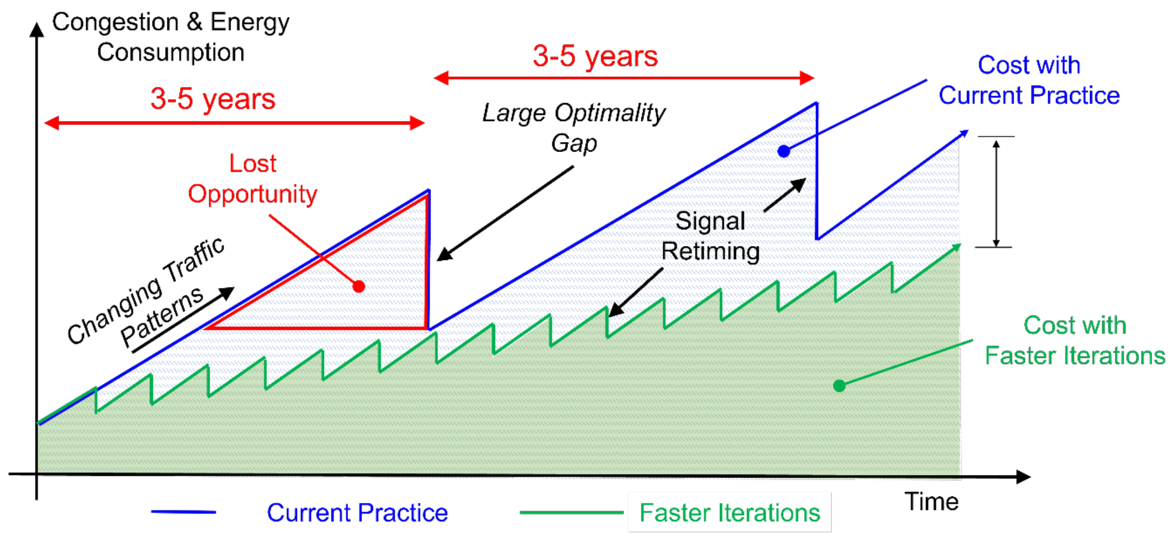



**Figure 1: Expected Benefits of More Iterative Retiming**

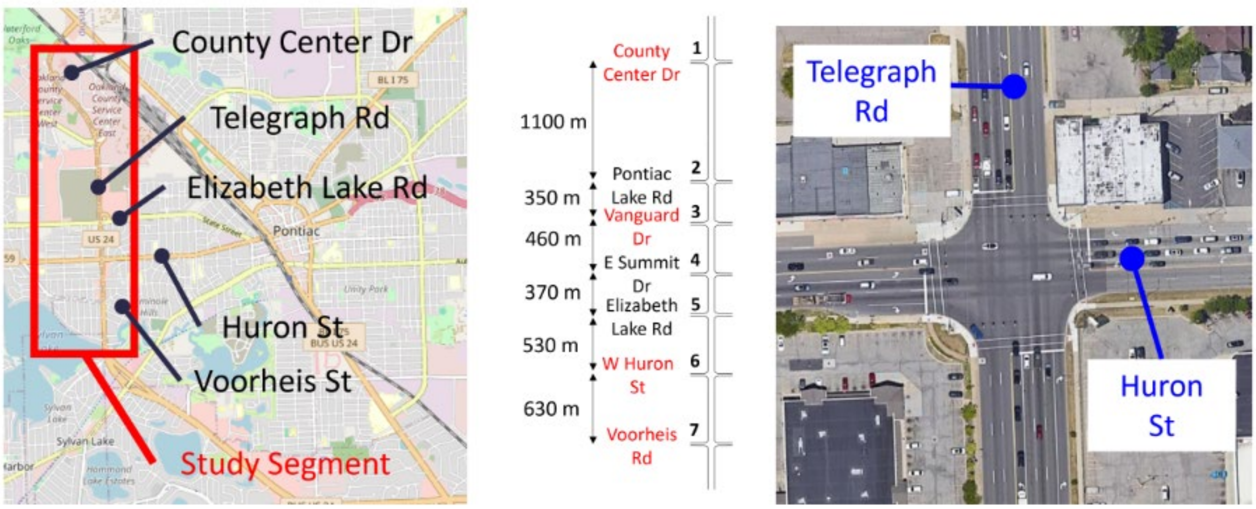
While many agencies have struggled to implement the "black-box" control strategies associated with ATSC for managing signal timing, fixed-point roadside detection systems can still offer valuable capabilities for monitoring current traffic dynamics and collecting SPMs. High resolution signal controller data (e.g., detector actuations and phase changes) provided by data logging controllers every tenth of a second can be converted into a variety of performance measurements known as ATSPMs. ATSPMs such as volumes, turning movement counts, AOG percentages, which evaluate the percentage of vehicles that have to stop before clearing the intersection, make it easier to identify signal timing issues (*26, 27*). Rather than just providing a temporary observation window, these performance measures collect data continuously, including weekends and off-peak times when performance is typically not assessed (*28*). However, physical infrastructure costs of around $50,000 for installation and $2,000 per year in maintenance have again prevented the widespread adoption of ATSPMs (*29*).

The prohibitive cost and ongoing maintenance of fixed-point roadside detection systems make it nearly impossible to monitor traffic dynamics at the more than 320,000 signalized intersections in the United States. As a result, data collection remains one of the chief bottlenecks to implementing responsive, large-scale traffic signal timing management. Today, most intersections lack any monitoring capability, preventing timely performance evaluations and retiming efforts. A traffic signal optimization system that leveraged vehicle trajectory data collected from crowd-sourced applications to automatically generate new signal timing plans could drastically shorten the time needed to generate new timing plans in response to evolving traffic patterns.

# Methodology

*Experimental Design*

The study was carried out at seven intersections along a 2.5-mile stretch of Telegraph Road from County Center Drive to Voorheis Street in Pontiac, Michigan (Figure 2 (a)). Both MDOT and RCOC were involved in the project as these seven intersections are owned by MDOT but maintained and managed by RCOC. The segment operates under coordinated-actuated control. The northbound and southbound directions each have two lanes in the northern half of the segment from County Center Drive to Elizabeth Lake Road, where they are then each converted into three lanes. Figure 2 (b) depicts the spacing (in meters) between each intersection. The street names in red font indicate intersections where at least one of the non-coordinated movements are operating on minimum or no recall, meaning that an ERG scenario is possible for the coordinated movements. Figure 2 (c) shows an aerial view of the intersection with the side street that has the highest volume (Huron St).




(a) Study Segment (b) Intersections (c) Intersection with Huron Street

**Figure 2: Telegraph Road Study Segment in Pontiac, MI**

Figure 3 outlines the implementation schedule and data used for both the traditional and vehicle trajectory-based signal optimizations. All new timing plans for both optimizations were reviewed and implemented by RCOC. The traditional optimization was executed by a hired consultant using Synchro/SimTraffic version 11 from 24-hour approach counts and turning-movement counts during the three peak periods for a typical weekday (7 AM to 9 AM, 11 AM to 1 PM, and 2 PM to 6 PM) on a Tuesday, Wednesday, or Thursday. It included timing plan schedules, flash schedules, vehicle and pedestrian clearance interval calculations, cycle lengths, splits, and offsets. The initial optimization plans occurred on November 21st, 2023, with some final adjustments taking place before a final implementation on February 21st, 2024.

To structure a comparison that was as fair as possible, the vehicle trajectory-based optimization utilized data from before the initial traditional optimization implementation on November 21st, 2023, to create initial optimized plans that were implemented on March 4th, 2025. Final optimized plans were implemented on July 1st, 2025, after analyzing the results of the first optimization. This study included everything from the traditional study except flash schedules and clearance interval calculations (vehicle and pedestrian). Neither study considered left-turn phasing analysis.

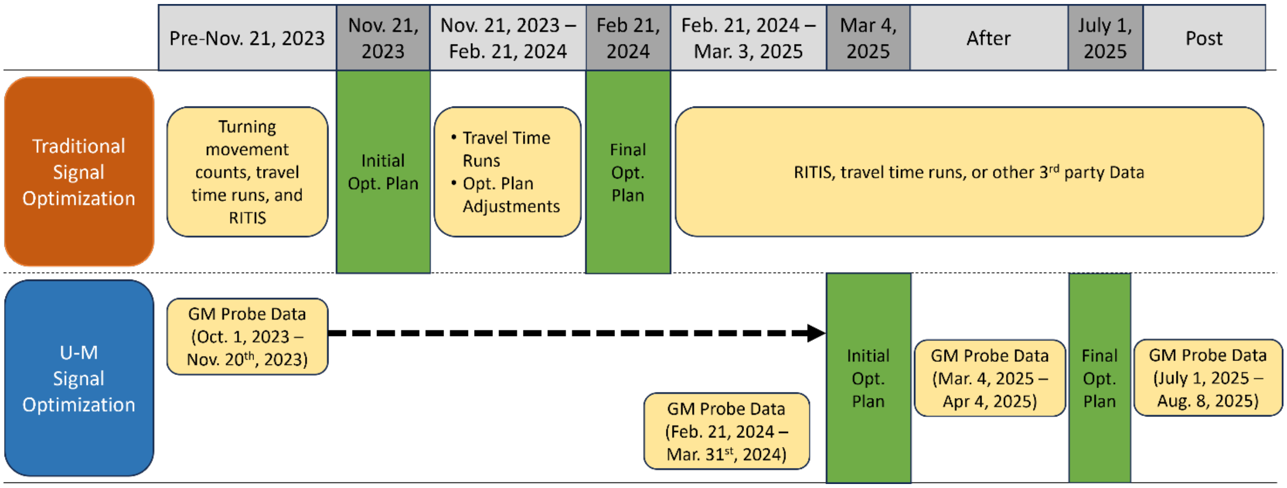



**Figure 3: Implementation Schedule**

*Equipment*

While no new equipment is evaluated in this project, this section will discuss the vehicle trajectory data and the procedure for the vehicle trajectory-based optimization method. This method is based on the probabilistic time-space (PTS) model, which can accurately reconstruct average recurrent traffic states by aggregating sufficient historical data, even at low penetration rates (*9*).

*Vehicle Trajectory Data*

Recently, Global Navigation Satellite System (GNSS) data from vehicles equipped with cloud or cellular services has become increasingly accessible through crowdsourced applications, including navigation tools, ride-hailing services, and roadside assistance platforms. Vehicle trajectory data—also known as probe or telematics data—from these vehicles has the potential to bring dynamic and responsive signal control solutions to millions of traffic signals around the world without the need for additional roadside sensors. It provides detailed travel-path information 24/7 across entire traffic networks, acting as mobile sensors enabling scalable performance monitoring capabilities. Even at limited vehicle observation rates, the temporal-spatial properties of vehicle trajectory data can give insights into the overall traffic performance Figure 4 plots GNSS points from observed vehicles in Birmingham, Michigan. The color of each point represents the speed, as indicated by the color bar on the right. Even at just the estimated 7% penetration (observation) rate of the total number of vehicles (*9*), the figure demonstrates how the speed information can give us a general understanding of the traffic dynamics across an entire network. As automation and connectivity increase on our traffic networks, there will be greater opportunity for vehicle trajectory-based traffic signal control.

Vehicle trajectory data provides traces of vehicle paths through time and space that can be leveraged to infer other traffic dynamics. Figure 5 (a) illustrates two examples of observed vehicles approaching an intersection on time-space diagrams. First, consider a vehicle trajectory that exhibits a stop some distance before the stop bar. Based on the stopping location, we can infer the number of vehicles queued ahead. Alternative, Figure 5 (b) illustrates how if we do not observe a stop in a vehicle trajectory, it indicates that a vehicle queue at the intersection did not impact that trajectory's path. Therefore, low observation rates can be overcome by leveraging the temporal-spatial information embedded in vehicle trajectory data.

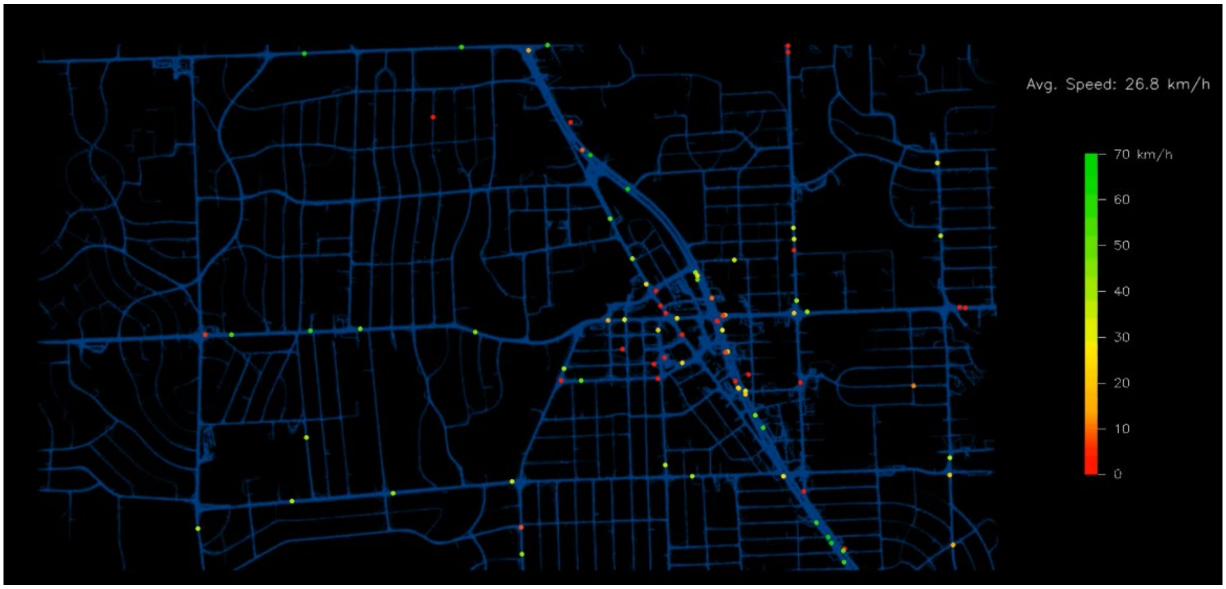
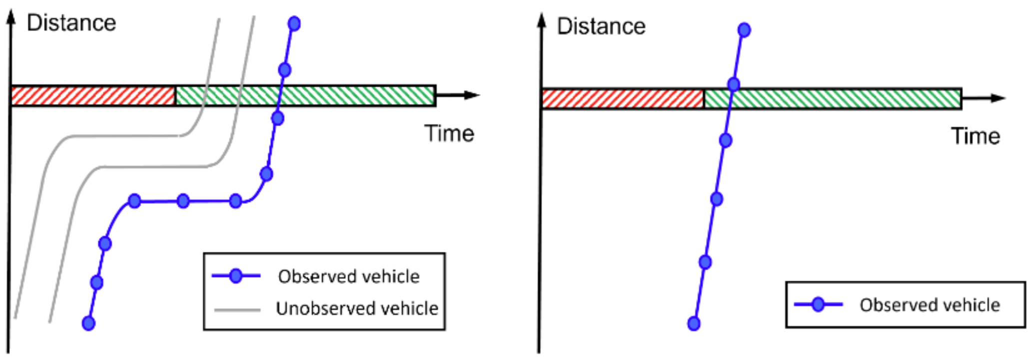



**Figure 4: GNSS Points from Observed Vehicles in Birmingham, MI**




(a) Unobserved vehicles queued ahead of observed vehicle

(b) No unobserved vehicles queued ahead of observed vehicle

**Figure 5: Leveraging Temporal-Spatial Information of Observed Vehicle Trajectories to Infer the Presence of Other Vehicles.**

The increasing availability of this data has bolstered the development of the next generation of traffic SPMs that expand upon the existing ATSPMs. Monitoring traffic through vehicle trajectory data is highly scalable due to its large coverage area, offering many advantages over fixed point detection methods used for ATSPMs (*5-8, 30*). It has a much larger coverage area than detector data because it is available at almost every intersection, especially those with higher traffic volumes. While detector data can only provide traffic counts and estimated speeds at certain locations, vehicle trajectory data spans the entire spatial-temporal space and provides more enriched SPMs such as control delay, number of stops, and travel path. Figure 6 plots a vehicle trajectory on a time-space diagram and illustrates how these SPMs are extracted. These measures can be aggregated for operational performance evaluations such as AOG percentages and level of service (LOS). A performance monitoring system built on trajectory-based performance measures does not require any additional roadside detection technology and is more resilient to equipment failure as it will not completely lose traffic monitoring capability at any specific location if one vehicle's transponder malfunctions.

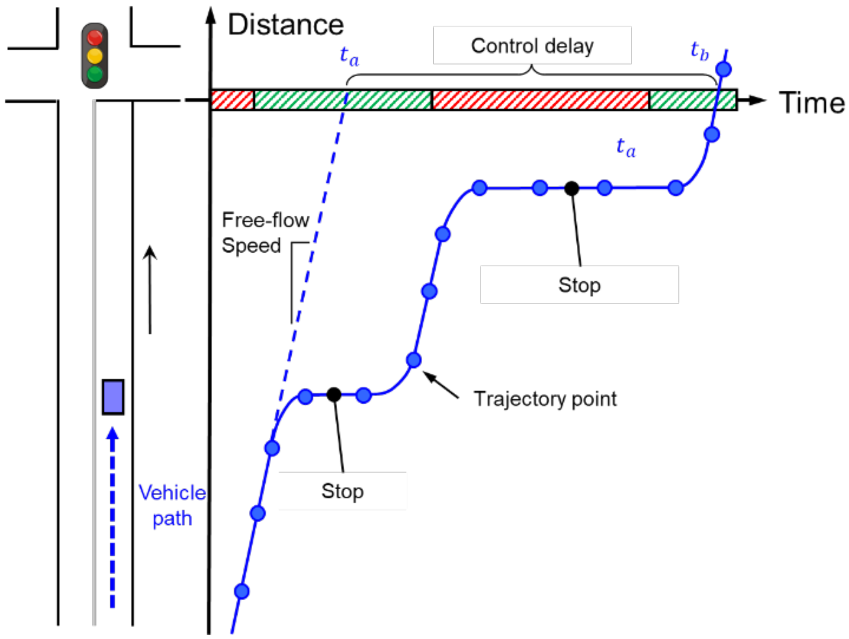



**Figure 6: Illustration of Vehicle Trajectory on Time-Space Diagram**

Existing performance monitoring systems with vehicle trajectory data offer valuable insights into existing congestion levels. However, these platforms lack robust modeling capabilities to forecast how traffic patterns would respond to different signal timing strategies. As a result, agencies are unable to fully leverage vehicle trajectory data in a predictive or optimization context, limiting its utility for proactive signal management.

*Probabilistic Time Space (PTS) Model*

Vehicle trajectory (vehicle trajectory) data has been used widely in the literature and in practice to evaluate traffic states at signalized intersection. Despite the limited vehicle trajectory observation (penetration) rates, the aggregated time-space diagram (Figure 7) has been used in the past to overcome this limitation. Figure 7 illustrates our own variation that leverages the cyclical nature of traffic signal parameters and traffic demand to depict an average (recurrent) traffic state of a particular movement. Other variations, such as the Purdue Performance Diagram (PPD), exist that do not include signal timing information (*6*). These diagrams serve very similar functions to other commercial solutions such as the arrival on green (AoG) graphs provided in the *Signal Analytics* platform provided by INRIX and the *ClearGuide Signals* platform provided by Iteris. While aggregating the observations is very useful for evaluating the performance of traffic signals, and in some cases can be used to adjust green splits (*10*), it has its limitations when used to optimize offsets and cycle lengths.

In order to optimize these crucial traffic signal parameters, we need a model that not only captures the current traffic state but also predicts future states under alternative signal timing plans. Traditional models (e.g., Synchro) require inputs such as speed, density, or volume measurements taken from detector data or turning movement counts and are not compatible with low penetration rate vehicle trajectory data (Figure 8). A prediction model for vehicle trajectory-based optimization needs to leverage the temporal-spatial advantages of vehicle trajectory data rather than simply the number of observations. A basic introduction to this concept is provided in Figure 5.

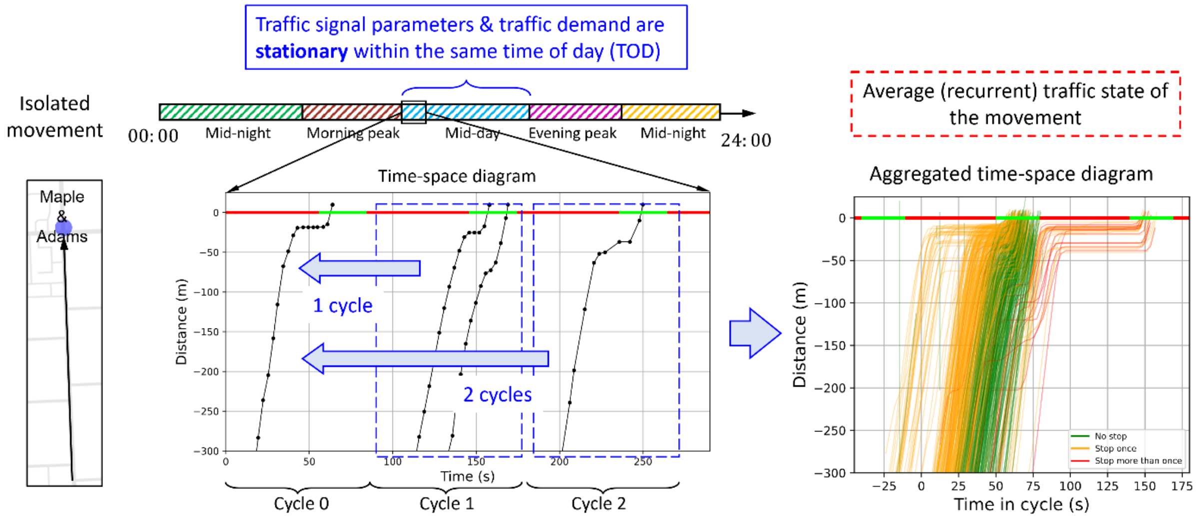



**Figure 7: Building the Aggregate Time-Space Diagram**

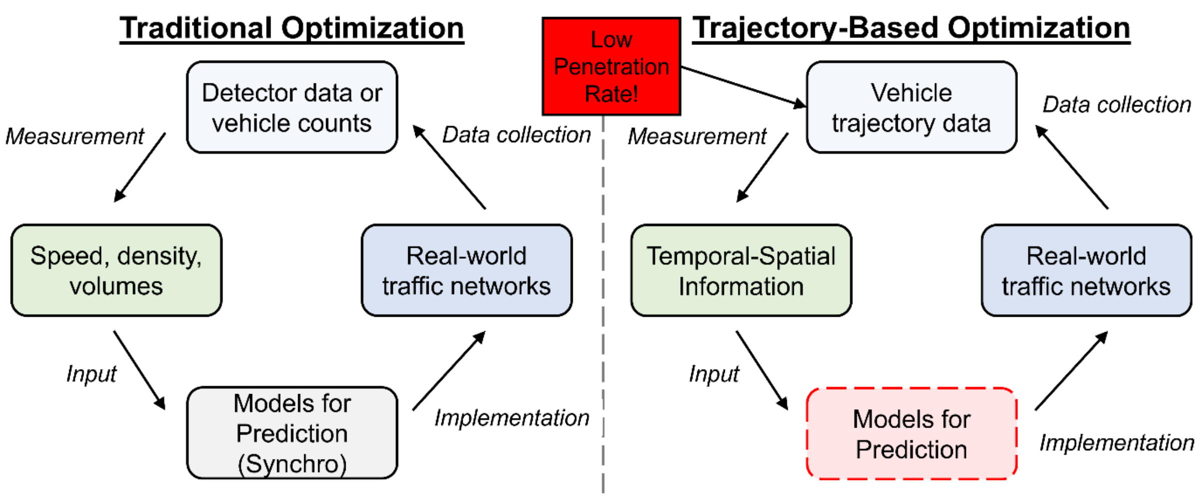



**Figure 8: Difference Between the current practice and the proposed vehicle trajectory-based method**

The PTS model introduced in our previous work was designed to fill this gap Wang et al. (*9*). Figure 9 provides an overview of the model's technical details. It is a stochastic traffic flow model built using a new coordinate system, the Newellian Coordinates, that can encode trajectories in a way that harnesses their temporal-spatial advantages (Figure 9 (a)). Newellian Coordinates assume that all vehicles follow a homogeneous deterministic Newell's car-following model in order to encode their trajectories according to their intersection arrival time and stop position in relation to the stop bar (*9, 31*) These coordinates are based on a distorted grid where the slope of the vertical axis is the free-flow speed $v_f$ (Figure 9 (a)). Therefore, vehicle trajectories are encoded in either a stop or free-flow state. This allows us to ignore the free-flow travel time and easily quantify delay resulting from traffic signal control.

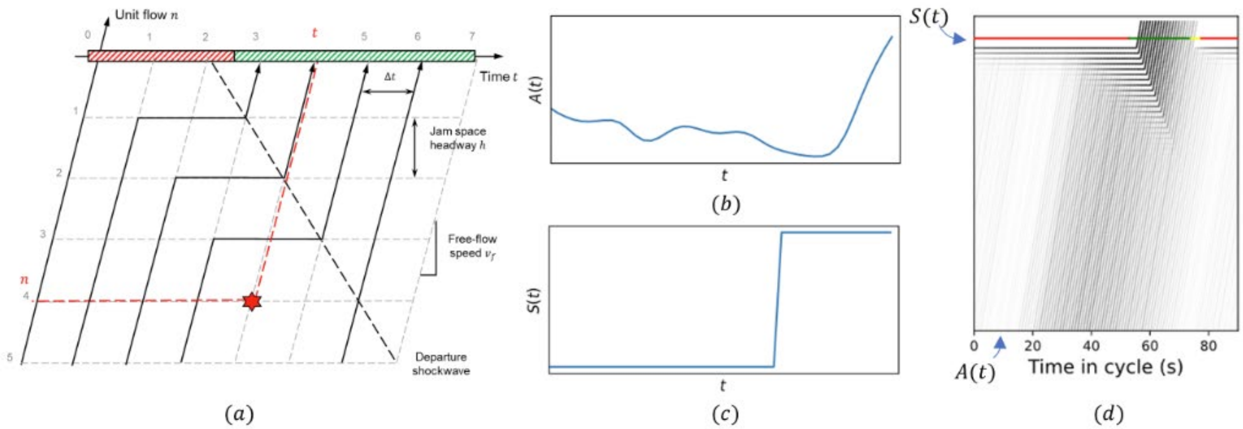
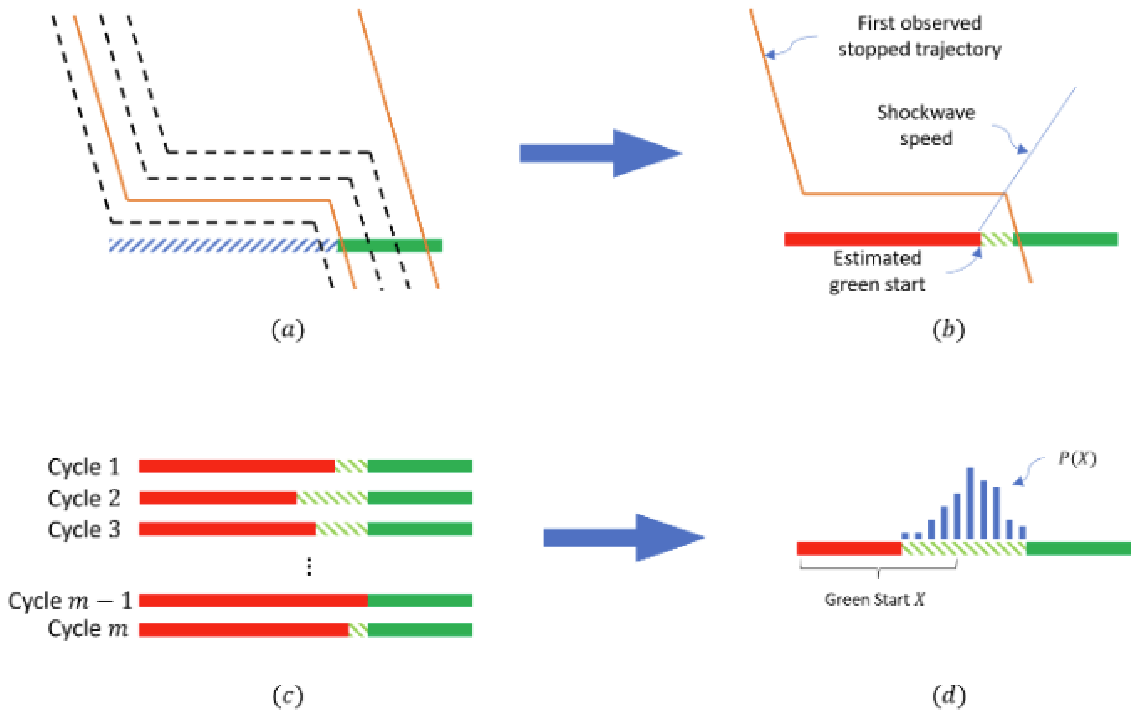



**Figure 9: Demonstration of Probabilistic Time-Space (PTS) Model. (a) Newellian coordinate system; (b) Arrival rate profile ( ); (c) Signal state ( ); (c) PTS diagram given arrival rate and signal state, drawn in the Newellian coordinates.**

We have demonstrated that a simple point-queue model under the proposed Newellian coordinates can sufficiently capture spatial-temporal traffic state through the PTS diagram. The main advantage of the model is that it is a stochastic model with low dimensions and can be directly calibrated by taking the vehicle trajectory data as the input. It enables us to apply different estimation algorithms to estimate unknown traffic states and parameters. Even at a low penetration rate, recurrent traffic states can be accurately reconstructed by aggregating sufficient historical data.

The PTS model accepts two primary inputs: the arrival rates $A(t)$ and the state of the traffic signal $S(t)$ within a cycle (Figure 9 (b) and (c)). As shown in Figure 9 (d), the PTS model can be visualized as the PTS diagram, which looks like the time-space diagram. However, unlike the time-space diagram, where each line represents a trajectory, the opacity of the line in the PTS diagram represents the probability of there being a vehicle. The model can be calibrated by scaling the arrival rate distribution (determined by the observed aggregated time space diagram in Figure 7) in way where the observed delay is equal to the delay predicted by the model. Once the model is calibrated, it can determine an optimal signal timing plan through delay predictions under a range of feasible alternatives.

In order to consider the actuated-coordinated setting, we must consider the possibility for early return to green (ERG), which occurs when the actual green start time of the coordinated movement occurs before the designated offset after non coordinated actuated movements gap out. Based on observed trajectory data, we can estimate the green start time of the coordination phase for each cycle. As shown in Figure 10 (a), suppose the cycle length is known for this movement. The designated green split is also known and is shown in green. The actual green start time is unknown, but we know it is somewhere in the blue diagonal-hatching area. The dashed black lines depict the unobserved trajectories, while the solid orange lines represent the observed trajectories. To estimate the actual green start in this cycle, we can find the first observed stopped trajectory and its point of departure. Draw a line through this point with a slope corresponding to the shockwave speed. Then, the intersection of this line with the stop bar represents the estimated green start time (Figure 10 (b)). So, the blue diagonal-hatching area in Figure 10 turns into red and green back-diagonal-hatching areas, which represent the red light and the extra green due to ERG, respectively. The shockwave speed can be estimated by aggregating trajectories in the fixed-time intersection into one cycle and fitting all the departure points with a robust linear regression algorithm.




In this way, we can obtain the green start distribution by aggregating the estimated green start time from multiple cycles. This process is illustrated by Figure 10 (c)-(d). We can then reflect the green start probability in the signal state $S(t)$ depicted in Figure 9 (c).

*Procedures*

We will now cover how the PTS model can be used to optimize timing plans, offsets, cycle lengths, and green splits. As an example, we demonstrate how these methods were executed on the Telegraph Road corridor segment.

*Timing Plan Schedules*

The first step in the signal timing optimization process is to evaluate the timing plan schedules. For this study, we were limited to the standard three time periods (AM, MD, and PM), so we only investigated the placement of their boundaries. Figure 11 depicts the trajectory histograms for the northbound and southbound movements along the corridor segment across the 24-hour period (aggregated from October 2nd, 2023, to October 20th, 2023). The black dashed line indicates the boundaries that did not change as part of the vehicle trajectory-based optimization. The red dashed lines indicate the original boundaries and the blue dashed line indicates new boundaries. The major changes included shifting the end of AM/beginning of MD from 10 to 9 and shifting the end of MD/beginning of PM from 15 to 14. The 10 to 9 shift was chosen because the observations in the middle of the day started to level out starting at 9. The 15 to 14 shift was chosen because the PM peak pattern seems to start building at 14 in the northbound direction.

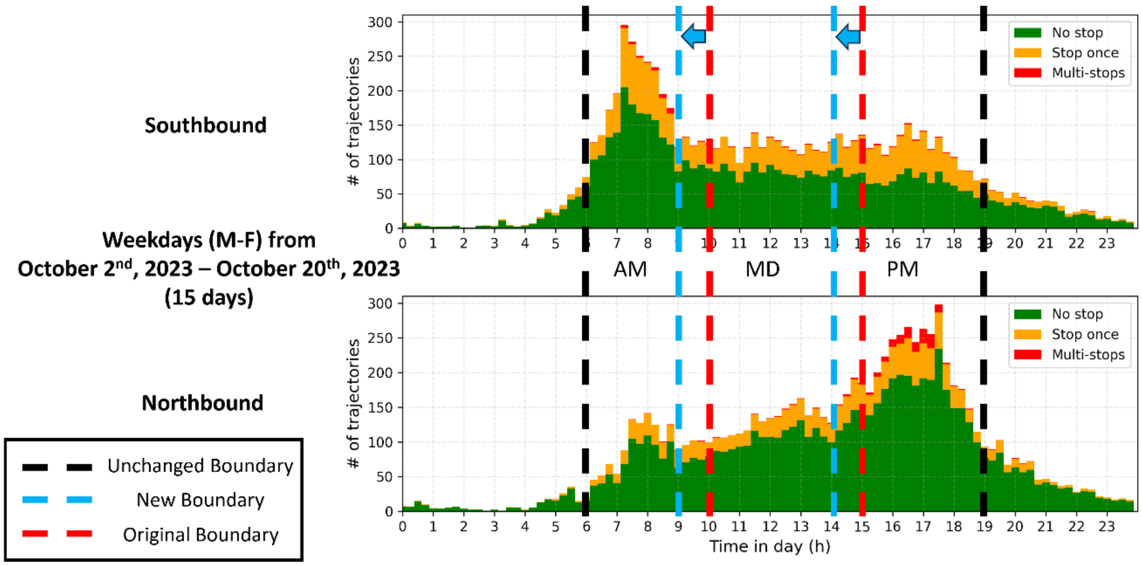



**Figure 11: Trajectory Histograms for Northbound and Southbound Movements Along Corridor Segment Across 24-hour Period and Timing Plan Schedule Changes**

*Offsets*

The offsets are optimized using the PTS model. In order to not overlap with any of the timing plan schedule changes, the aggregation time periods (time ranges where trajectories were extracted to build model for each time period) were limited to 7-9, 10-14, and 15-18 for the AM, MD, and PM time periods, respectively. A demonstration of how this works is shown in Figure 12. Note that the orange color on the signal bar indicates the range of possibility for an ERG scenario based on the minimum service times of the other movements. The top left figure illustrates the aggregated time-space diagram for the entire corridor, which is built by stacking the aggregated time-space diagram for each intersection. The corridor is depicted through the PTS diagram in Figure 12 (b). Note how the ERG is accounted for in the model through departures during the orange band, particularly at Vanguard Drive. The model for this particular direction is calibrated by matching the observed average delay with the model estimated average delay. In general, a match within 1-2 seconds is sufficient. Next, the bottom right figure (d) illustrates the predicted performance after the optimization. This optimization provides the new offsets. It is easy to see how coordination is improved in the optimized PTS diagram. In this case, the model predicts a reduction in delay from 15.5 seconds to 8.8 seconds (43.2%). To complete the visualization of this process, we have gone ahead and included the observation after the optimization of the vehicle trajectory-based implementation in this figure in the bottom left (c).

*Cycle Length*

The PTS model can also be used to model changes in cycle length. Table 1 reports the predicted average control delay per coordinated movement considering different cycle lengths in the MD time period. This particular time period is of interest because the traditional optimization chose to increase the cycle length from 100 seconds (current) to 120 seconds. The green split ratios in relation to the cycle were kept constant for each cycle length evaluation. According to the PTS model, the 100 second cycle length was determined to still be the optimal cycle length for the MD time period.

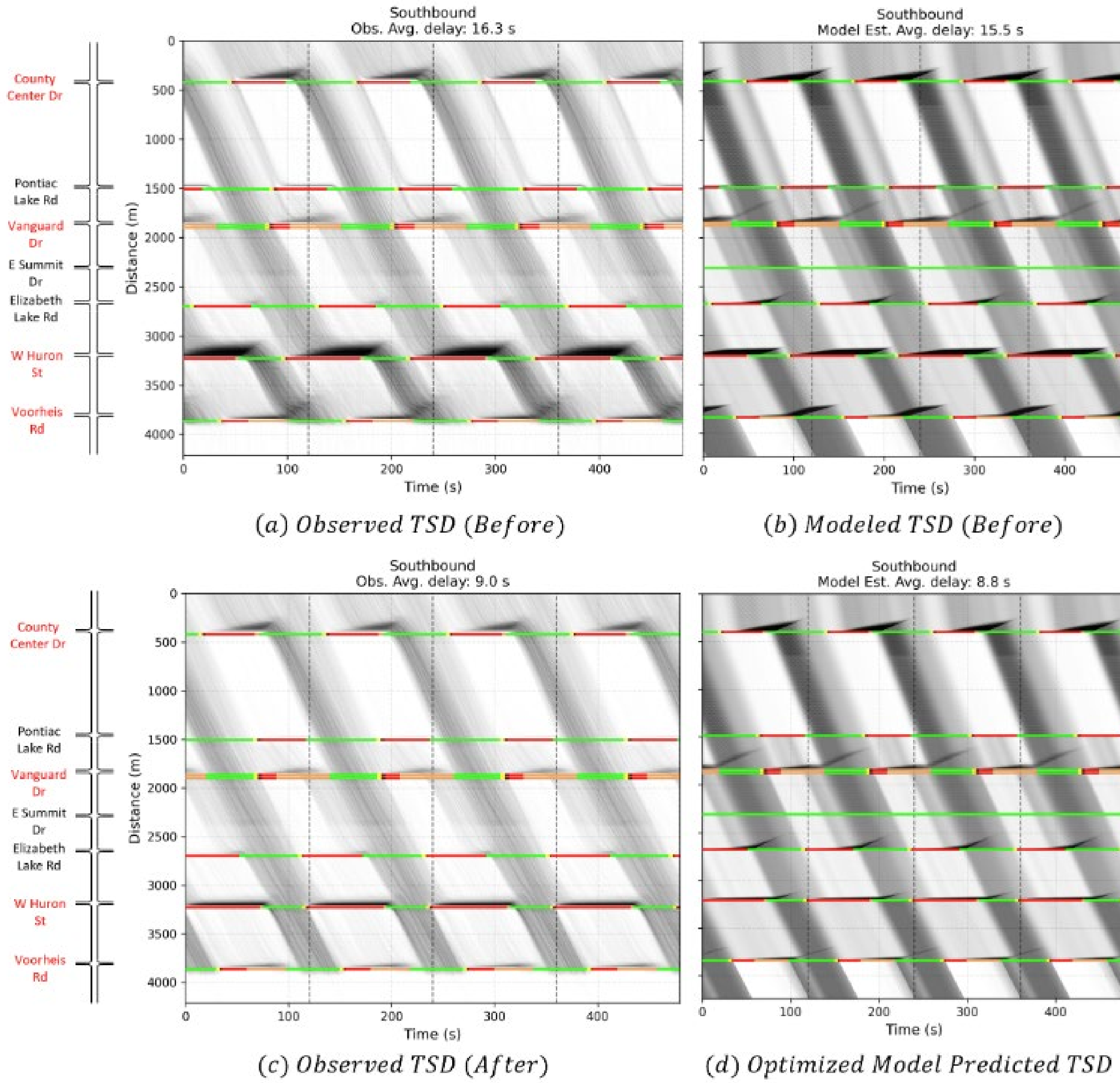



**Figure 12: Observed and Modeled Time-Space Diagrams (TSDs) of Telegraph Road During the AM Time Period Before and After Vehicle Trajectory-Based Optimization**

A comparison of the timing plan schedules and optimized cycle lengths for both optimizations are provided in Table 2. Plan 2 is associate with the AM period, Plan 1 is associated with the MD period, and Plan 3 is associated with the PM period. While the vehicle trajectory-based optimization changed the timing plan schedules, the cycle lengths were kept constant for their respective period names. The traditional optimization also decided to change the end of MD/beginning of PM from 15 to 14 but did not pursue the 10 to 9 change.

**Table 1: Prediction of Average Control Delay per Movement (s) Along Coordinated Movements for Different Cycle Lengths During the MD Time Period**

| Cycle | Northbound | Southbound | Both |
|---|---|---|---|
| 80 | 6.6 | 10.6 | 8.5 |
| 90 | 7.5 | 10.0 | 8.7 |
| 100 | 7.0 | 9.7 | 8.3 |
| 110 | 8.3 | 10.3 | 9.3 |
| 120 | 7.4 | 13.9 | 10.4 |

**Table 2: Summary of Timing Plan Schedule Changes and Cycle Lengths**

| Time Range | Orig. Plan | Orig. Cycle | Trajectory-Based Plan | Trajectory-Based Cycle | Traditional Plan | Traditional Cycle |
|---|---|---|---|---|---|---|
| 6-9 | Plan 2 (AM) | 120s | Plan 2 (AM) | 120s | Plan 2 (AM) | 120s |
| 9-10 | Plan 2 (AM) | 120s | Plan 1 (MD) | 100s | Plan 2 (AM) | 120s |
| 10-14 | Plan 1 (MD) | 100s | Plan 1 (MD) | 100s | Plan 1 (MD) | 120s |
| 14-15 | Plan 1 (MD) | 100s | Plan 3 (PM) | 120s | Plan 3 (PM) | 100s |
| 15-19 | Plan 3 (PM) | 120s | Plan 3 (PM) | 120s | Plan 3 (PM) | 120s |

*Green Splits*

Green splits were adjusted heuristically by identifying oversaturated movements according to high split failure ratios (Figure 13 (a)). "Donor" movements were identified by isolating trajectories that only stop once (orange) and the available green time before these vehicles start to experience split failures (Figure 13 (b)). The limitation to this method is that as we reduce the green time the number of one stop vehicles will increase. Therefore, green split adjustments were limited to 4 seconds. This project plans to execute a second round of optimization (Figure 3), so the green splits can be adjusted again if the 4 second maximum is too restrictive. Intersections with no oversaturated movements were rebalanced to give more green time to Telegraph Road based on available "donor" movements. Pedestrian minimums were used as a constraint where required.

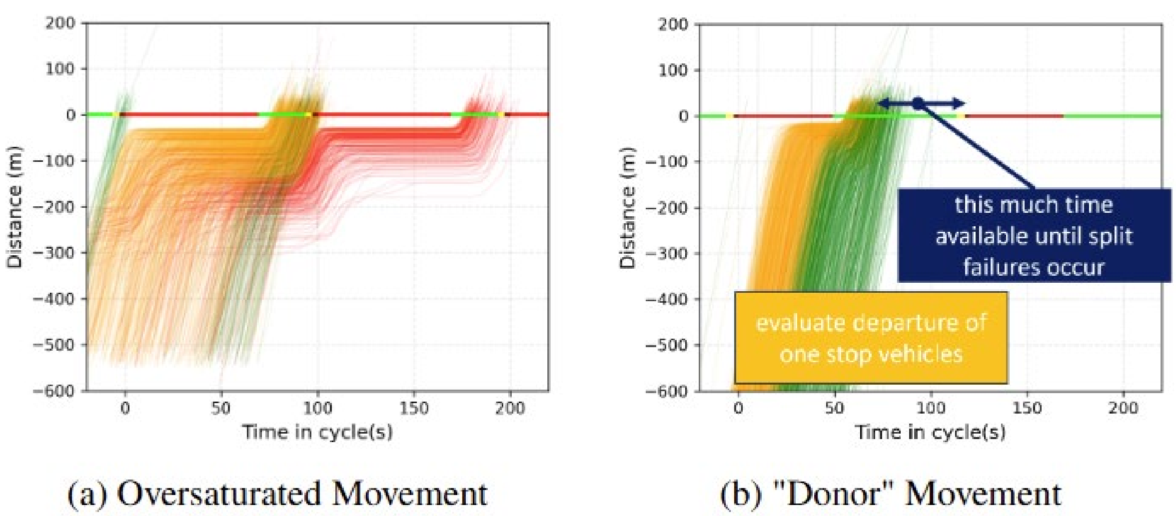



**Figure 13: Green Split Adjustment Methodology**

# Findings

*Summary of Data*

In the vehicle trajectory-based optimization, the road network was re-organized from the open-source online resource OpenStreetMap (*32*). Each trajectory is matched to the road network and then the raw Global Navigation Satellite System (GNSS) coordinates are converted to distance information (*7, 33*). Vehicle trajectory data was provided for the dates listed in Figure 3 by a major automotive original equipment manufacturer (OEM), who equips their vehicles with GNSS receivers and inertial measurement units (IMUs) that provide accurate vehicle position and dynamics information. Trajectory points are received approximately every 3 seconds and include a unique, anonymized trip ID, GNSS coordinates (latitude and longitude), timestamp, and speed. The coordinates are accurate to roughly within 3-5 meters. The penetration rate is estimated to be around 7% in the study area (*9*). RCOC provided the current signal timing parameters.

*Method of Analysis*

To conduct the before and after analysis for both the traditional and vehicle trajectory-based optimizations, this study utilized 24-hour weekday vehicle trajectory data from the following dates:

- Before: October 2nd, 2023, to October 27th, 2023
- After traditional optimization: March 4th, 2024, to March 28th, 2024
- After initial vehicle trajectory-based optimization: March 10th, 2025, to March 28th, 2025
- After final vehicle trajectory-based optimization: July 31st, 2025, to August 8th, 2025

We acknowledge that the review schedule includes a significant time gap between the before and after study for the vehicle trajectory-based optimization. We believe that using data collected prior to the traditional optimization—both to generate and evaluate the vehicle trajectory-based optimization—was a necessary decision to ensure a fair comparison between the two signal timing plans. The extended duration between the before and after periods reflects a practical trade-off inherent in conducting real-world implementations. Additionally, the time period for trajectory data after the final trajectory-based optimization is only about one week long due to unexpected culvert maintenance at the intersection of Telegraph Rd. and Pontiac Lake Rd. from the end of June through mid-July. Figure 14 illustrates the resulting lane closures as a result of this maintenance, as confirmed by MDOT. Figure 15 plots the average control delay over time for the AM, MD, and PM time periods to illustrate the impacts the lane closer had on congestion levels during construction. Therefore, the after analysis for the final trajectory-based optimization only includes one week of data from when the lane closures were completed.

To evaluate the performance of each movement at each intersection along the corridor, we utilize three common performance measures: control delay, number of stops, and split failures (Figure 16 (a)). These measures are extracted from individual vehicle trajectories and then averaged by movement, intersection, and across the entire corridor. While this method is effective for assessing movement-level performance, traffic agencies often rely on GPS travel time runs to evaluate signal coordination. Traditionally, this involves manual data collection, with a driver conducting 5–10 runs along the corridor using an onboard GPS receiver. In contrast, crowdsourced-vehicle trajectory data enables the extraction of hundreds of travel time runs with minimal effort. For example, Figure 16 (b) shows 403 observations collected between 7 AM and 9 AM over the course of a week. This not only simplifies data collection but also yields more statistically robust travel time averages. Note that the orange color on the signal bar indicates the range of ERG possibilities based on minimum service times of the other movements.

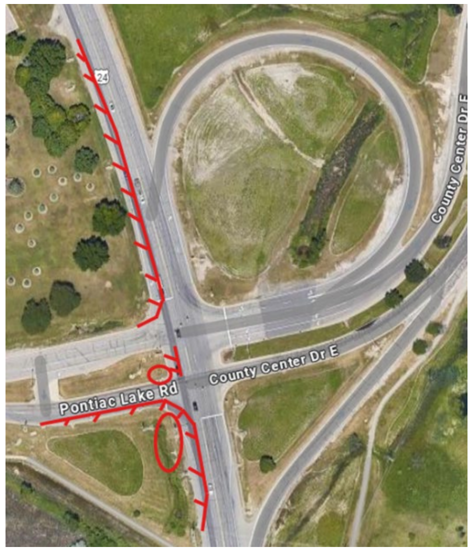



**Figure 15: Diagram of lane closures during construction at Telegraph Rd. and Pontiac Lake Rd.**

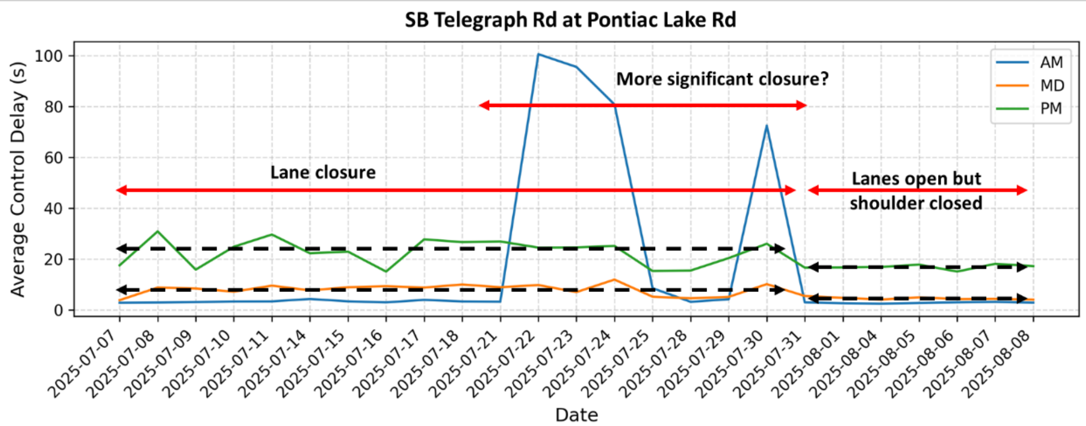
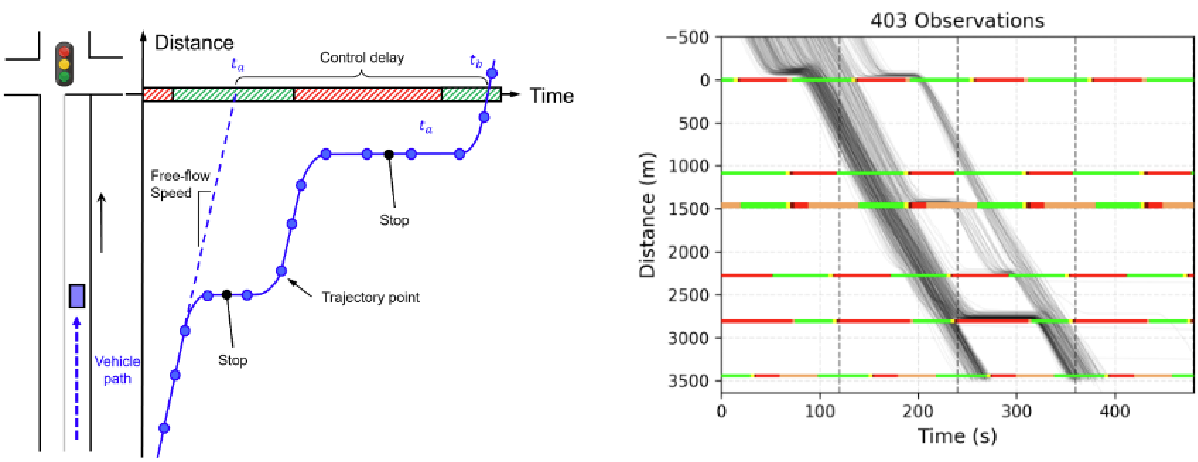



**Figure 14: Control Delay Analysis for AM, MD, and PM Time Periods to Evaluate Impacts of Construction**




(a) Intersection Performance Measures

(b) Corridor Travel Times

**Figure 16: Signal Timing Performance Analysis Using Vehicle Trajectory Data**

*Presentation of Results (After Initial-Optimization)*

Both optimizations performed relatively the same for the northbound direction, reducing travel times from 263 seconds to 242 and 240 seconds. However, the vehicle trajectory-based optimization out-performed the traditional optimization in the southbound direction, where the average travel times were reduced from 293 seconds to 258 seconds (11.8%) compared to the traditional optimization reduction to 275 seconds (6.3%). Table 3 also breaks down the results by time period, isolating hours 9-10 and 14-15 because of the timing plan schedule changes executed by both optimizations. While the magnitude varies, the vehicle trajectory-based optimization performed better than the traditional optimization in every time period. The biggest difference was during the AM time period, where the vehicle trajectory-based optimization reduced travel times by 47 seconds compared to a 32 reduction by the traditional optimization. Another comparison point of interest is the 9-10 hour because the vehicle trajectory-based optimization changes the timing plan schedule by starting the MD timing plan at 9. The vehicle trajectory-based optimization reduced travel time by 30 seconds during this hour, compared to a 22 second reduction by the traditional optimization.

Table 3 reports the average corridor travel times before and after each optimization. Overall, the vehicle trajectory-based optimization reduced average corridor travel times by around a half a minute (9.9%), slightly better than the traditional optimization, which reduced travel times by around 7.6%.

**Table 3: Average Corridor Travel Time (s) by Time Period Before and After Initial Vehicle Trajectory-based and Traditional Optimizations (Weekdays)**

| Time Range | Direction | Before | After Trajectory-based Optimization (% Change) | After Traditional Optimization (% Change) |
|---|---|---|---|---|
| 24-hours | Northbound | 263 | 242 (-8.2%) | 240 (-8.7%) |
| | Southbound | 293 | 258 (-11.8%) | 275 (-6.3%) |
| | Both | 277 | 250 (-9.9%) | 256 (-7.6%) |
| 6-9 (AM) | Both | 288 | 241 (-16.3%) | 256 (-11.3%) |
| 9-10 | Both | 276 | 246 (-11.0%) | 254 (-8.0%) |
| 10-14 (MD) | Both | 257 | 252 (-1.8%) | 256 (-0.2%) |
| 14-15 | Both | 264 | 258 (-2.1%) | 262 (-0.7%) |
| 15-19 (PM) | Both | 309 | 263 (-14.8%) | 264 (-14.3%) |

While travel time runs are great for analyzing the experience of vehicles that traverse the entire corridor, it is possible that traffic volumes may not be evenly distributed at each intersection along the segment of interest as vehicles may turn off the corridor at various points. Therefore, Table 4 presents the average control delay per movement for the northbound and southbound directions along the study segment. The reported values are weighted averages, accounting for the number of observations at each movement, to more accurately represent the delay experienced along each coordinated direction. For the 24-hour period, the vehicle trajectory-based optimization reduced the control delay by 17.2% from 13.5 seconds to 11.2 seconds, as opposed to a 14.5% decrease by the traditional optimization. The vehicle trajectory-based optimization again performed better than the traditional optimization in every time period except the 14-15 hour. There was a minimal difference during the 9-10 hour between the two optimizations, indicating no real advantage for shifting the MD time period start time to 9. The MD period (10-14) is also of particular note because each optimization strategies chose different cycle lengths. The traditional optimization, which increased the cycle length from 100 seconds to 120 seconds, resulted in a 6.6% increase in the average control delay, while the vehicle trajectory-based optimization, which kept the cycle length at 100 seconds, resulted in a slight decrease (2.7%) in the average control delay. This result demonstrates the vehicle trajectory-based optimization's ability to evaluate different cycle lengths during the optimization process, as the decision to not increase the cycle length proved to be more beneficial for coordination.

**Table 4: Average Control Delay per Movements (s) Along Coordinated Movements by Time Period Before and After Initial Vehicle Trajectory-based and Traditional Optimizations (Weekdays)**

| Time Range | Direction | Before | After Trajectory-based Optimization (% Change) | After Traditional Optimization (% Change) |
|---|---|---|---|---|
| 24-hours | Northbound | 11.3 | 9.6 (-15.0%) | 9.3 (-17.7%) |
| | Southbound | 15.9 | 12.8 (-19.5%) | 13.9 (-12.6%) |
| | Both | 13.5 | 11.2 (-17.2%) | 11.5 (-14.5%) |
| 6-9 (AM) | Both | 14.9 | 10.8 (-27.3%) | 11.4 (-23.1%) |
| 9-10 | Both | 13.9 | 10.5 (-24.4%) | 10.6 (-23.5%) |
| 10-14 (MD) | Both | 11.3 | 11.0 (-2.7%) | 12.1 (+6.6%) |
| 14-15 | Both | 12.7 | 12.3 (-3.3%) | 12.3 (-3.1%) |
| 15-19 (PM) | Both | 16.8 | 12.9 (-23.2%) | 12.5 (-25.5%) |

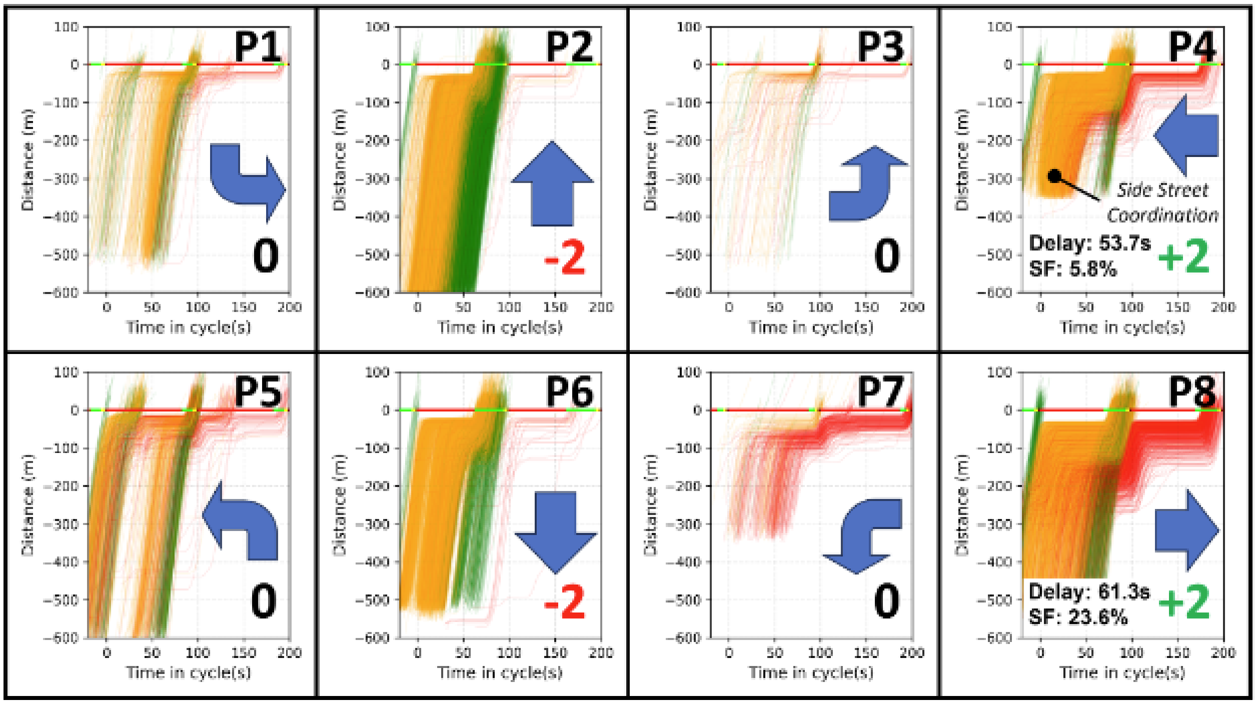
Finally, we report the changes in average control delay and number of stops per movement for all movements (including left turns and side street movements) in Table 5. The vehicle trajectory-based system outperformed the traditional approach for the 24-hr time range, reducing the overall control delay by 17.4% and the number of stops by 20.4%, compared to reductions of 13.7% and 14.9%, respectively, achieved by the traditional optimization. Again, we draw special attention to the 9-10 period because of the timing plan schedule change. While the reduction in control delay is slightly larger in the vehicle trajectory-based optimization, the traditional optimization achieved a greater reduction in number of stops. This is not completely surprising because the traditional optimization has a 120 second cycle length during the AM timing plan while the MD timing plan had a 100 second cycle length and increases in cycle length generally resulted in decreases in the number of stops. For the MD period from 10-14, the vehicle trajectory-based optimization reduced control delay by a full 3 seconds compared to only 0.2 seconds in the traditional. It also reduced the number of stops by 0.07 compared to 0.04. The greater reduction in stops by the vehicle trajectory-based optimization was unexpected because of the shorter cycle length. However, a closer look at one intersection not only provides an explanation for the decrease in number of stops, but also why the vehicle trajectory-based optimization performed much better in terms of control delay as well.

Figure 15 illustrates aggregated time-space diagrams for all movements at the intersection of Telegraph Road and Huron Street (depicted in Figure 15 (c)) for the MD time period before and after the vehicle trajectory-based optimizations. The diagrams are arrayed according to the intersection's dual-ring phase diagram sequencing. The numbers in the bottom right hand corner of each diagram indicate the green split changes implemented by the optimization. Additionally, while not reflected in these diagrams, the offset was increased by 50 seconds (or -50 seconds given 100 cycle length). The bottom left hand corner of phases 4 and 8 (far right of each dual-phase diagram) reports the changes in delay and split failures (SFs) as a result of the green split increase. Visually, it is very easy to notice the reduction in red, indicating trajectories that stopped twice before clearing the intersection. While the green split changes alone resulted in split failure reductions (phase 8 dropped from 23.6% split failures to 8.5%), it is also interesting to note how the offset change, designed for improving coordination on the Telegraph Rd, resulted in improved coordination for the westbound movement (phase 4) on Huron St. The call outs on the diagrams note how, because of the 50 second increase in the offset, the upstream platoon is not arriving during the green band but rather at the beginning of the red interval. This is also shown by there being more trajectories colored green, indicating those that did not have to stop before clearing the intersection. As a result, not only did the number of stops greatly reduce, but the delay was reduced by almost 40 seconds (73.6%). This result would not have been possible if the cycle length had increased to 120 seconds, because the coordination would have gone out of sync with the 100 second cycle lengths set on Huron St. This example highlights the power of using vehicle trajectory data to evaluate the network implications of signal coordination optimization.

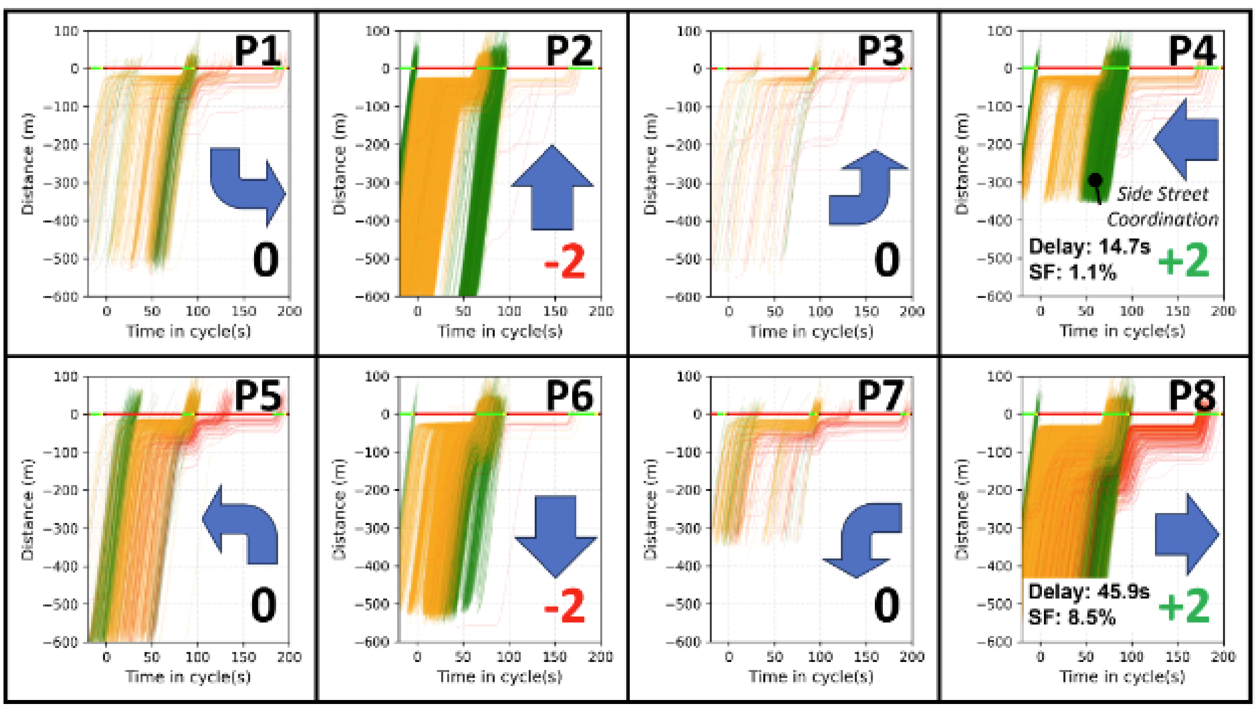
**Table 5: Average Control Delay and Number of Stops per Movement for All Movements by Time Period Before and After Initial Vehicle Trajectory-based and Traditional Optimizations (Weekdays)**

| Time Range | Direction | Before | After Trajectory-based Optimization (% Change) | After Traditional Optimization (% Change) |
|---|---|---|---|---|
| 24-hours | Control Delay (s) | 21.8 | 18.0 (-17.4%) | 18.8 (-13.7%) |
| | Number of stops | 0.44 | 0.35 (-20.4%) | 0.38 (-14.9%) |
| 6-9 (AM) | Control Delay (s) | 24.2 | 18.9 (-21.7%) | 19.7 (-18.5%) |
| | Number of stops | 0.47 | 0.35 (-20.8%) | 0.39 (-16.8%) |
| 9-10 | Control Delay (s) | 21.1 | 17.2 (-18.5%) | 17.2 (-18.7%) |
| | Number of stops | 0.43 | 0.37 (-15.1%) | 0.35 (-18.8%) |
| 10-14 (MD) | Control Delay (s) | 18.4 | 15.4 (-16.7%) | 18.2 (-1.2%) |
| | Number of stops | 0.41 | 0.34 (-17.8%) | 0.37 (-11.5%) |
| 14-15 | Control Delay (s) | 21.4 | 18.6 (-12.9%) | 18.9 (-11.3%) |
| | Number of stops | 0.48 | 0.36 (-25.2%) | 0.40 (-17.2%) |
| 15-19 (PM) | Control Delay (s) | 26.6 | 22.6 (-15.14%) | 21.1 (-20.9%) |
| | Number of stops | 0.50 | 0.41 (-18.9%) | 0.42 (-16.5%) |

*Presentation of Results (After Final Optimization)*




(a) Before




(b) After

**Figure 17: Time-Space Diagrams Before and After Vehicle Trajectory-based Optimizations for Each Movement at Telegraph Road and Huron Street for the MD Time Period**

**Table 6: Average Control Delay per Movements (s) Along Coordinated Movements by Time Period Before and After Final Vehicle Trajectory-based and Traditional Optimizations (Weekdays)**

| Time Range | Direction | Before | After Trajectory-based Optimization (% Change) | After Traditional Optimization (% Change) |
|---|---|---|---|---|
| 24-hours | Northbound | 11.3 | 11.3 (0.3%) | 9.3 (-17.7%) |
| | Southbound | 15.9 | 12.5 (-21.4%) | 13.9 (-12.6%) |
| | Both | 13.5 | 11.9 (-11.9%) | 11.5 (-14.5%) |
| 6-9 (AM) | Both | 14.9 | 10.2 (-31.6%) | 11.4 (-23.1%) |
| 9-10 | Both | 13.9 | 10.4 (-17.9%) | 10.6 (-23.5%) |
| 10-14 (MD) | Both | 11.3 | 11.7 +3.5%) | 12.1 (+6.6%) |
| 14-15 | Both | 12.7 | 13.5 (+6.6%) | 12.3 (-3.1%) |
| 15-19 (PM) | Both | 16.8 | 14.7 (-12.8%) | 12.5 (-25.5%) |

**Table 7: Average Control Delay and Number of Stops per Movement for All Movements by Time Period Before and After Final Vehicle Trajectory-based and Traditional Optimizations (Weekdays)**

| Time Range | Direction | Before | After Trajectory-based Optimization (% Change) | After Traditional Optimization (% Change) |
|---|---|---|---|---|
| 24-hours | Control Delay (s) | 21.8 | 18.2 (-16.3%) | 18.8 (-13.7%) |
| | Number of stops | 0.44 | 0.36 (-18.6%) | 0.38 (-14.9%) |
| 6-9 (AM) | Control Delay (s) | 24.2 | 18.0 (-25.7%) | 19.7 (-18.5%) |
| | Number of stops | 0.47 | 0.35 (-26.7%) | 0.39 (-16.8%) |
| 9-10 | Control Delay (s) | 21.1 | 17.2 (-18.5%) | 17.2 (-18.7%) |
| | Number of stops | 0.43 | 0.38 (-12.5%) | 0.35 (-18.8%) |
| 10-14 (MD) | Control Delay (s) | 18.4 | 15.9 (-13.8%) | 18.2 (-1.2%) |
| | Number of stops | 0.41 | 0.35 (-15.1%) | 0.37 (-11.5%) |
| 14-15 | Control Delay (s) | 21.4 | 20.1 (-5.8%) | 18.9 (-11.3%) |
| | Number of stops | 0.48 | 0.38 (-19.8%) | 0.40 (-17.2%) |
| 15-19 (PM) | Control Delay (s) | 26.6 | 23.4 (-12.1%) | 21.1 (-20.9%) |
| | Number of stops | 0.50 | 0.42 (-15.8%) | 0.42 (-16.5%) |

*Benefit/Cost Analysis*

Table 6 reports a cost comparison between the traditional optimization project on Telegraph Road to an estimate of the vehicle trajectory-based optimization based on this research. The traditional project took place along 45 intersections on Telegraph Road from I-696 to Dixie Highway. On average data collection cost $850 per intersection, the consultant review and analysis cost $3,720 per intersection, and the review and implementation by RCOC cost $570 per intersection. This project included crash analysis, signal warrant analysis, and clearance interval calculation, all of which were not included in the vehicle trajectory-based implementation. Therefore a 0.75 scaling factor was applied to the consultant review and analysis fee to estimate the costs of the tasks which were executed in both optimizations. After applying this scaling factor, the total cost for the traditional retiming was $4,210 per intersection.

**Table 8: Cost per Inetsection Comparison between Traditional and Vehicle Trajectory-Based Optimization**

| Task | Traditional | Trajectory-Based | % Difference |
|---|---|---|---|
| Data Collection | $850 | $334 | -60.7 |
| Trajectory-Based Optimization and Analysis | - | $1,600 | -33.7 |
| Consultant Review and Analysis | $3,720 x 0.75 = $2,790 | $250 | |
| Review and Implementation by RCOC | $570 | $570 | - |
| Total | $4,210 | $2,754 | -34.6 |

Vehicle trajectory data in this project was provided by General Motors (GM) Research and Development. However, GM currently does not offer a commercial product for the necessary vehicle trajectory data needed to execute this type of optimization. One such option is provided by Streetlight through their Connected Vehicle Journey Data. For the 3 months of data needed to execute the optimization performed in this project (before, after iteration 1, after iteration 2), UM received a quote for $14,520.75 for the entire county. Currently, the county is the smallest jurisdictional area available for purchase. If MDOT were to use this data for the 45 intersections in the project, it would come out to $333.68 per intersection, representing a 60.7% decrease in cost for data alone. We estimate a $1,600 fee for the trajectory-based optimization and analysis provided by the system developed in this project, along with a $250 fee for consultant review and analysis. The review and implementation by RCOC would remain the same. The final cost for the vehicle trajectory-based optimization is $2,754, a 34.6% decrease in cost compared to the traditional.

Traditional traffic signal optimization is widely regarded by traffic engineers as one of the most cost-effective methods for reducing congestion and energy consumption, with some project reporting benefit-to-cost ratios between 24:1 and 83:1 (*2-4, 34*). Considering that the performance of the vehicle trajectory based optimization system was comparable to the traditional, we believe the cost savings would result in improved benefit-to-cost ratios. However, this system also offers other distinct advantages to the traditional optimization procedure, including the ability to provide more targeted and frequent retiming interventions that maximize potential benefits. The quote above would include data from the entire Oakland County, giving MDOT an opportunity to monitor and identify retiming opportunities at hundreds of intersections at a fraction of the cost of traditional data collection methods.

## Conclusion

*Conclusions from the Study*

This section compares real-world implementations of our vehicle trajectory-based traffic signal optimization system and a traditional optimization. The implementation took place on a 2.5-mile stretch of a coordinated-actuated arterial with seven intersections in Pontiac, Michigan. Both optimizations retimed signal timing plan schedules, cycle lengths, offsets, green splits. However, the traditional optimization used vehicle count data while the vehicle trajectory-based optimization used a small percentage of vehicle trajectory data as the only input.

Besides different offsets and green split decisions between the vehicle trajectory-based and traditional optimizations, the optimizations differed in two key aspects. First, the vehicle trajectory-based optimization chose to move the end of the AM/beginning of the PM from hour 10 to 9. Both optimizations moved the end of MD/beginning of PM from hour 15 to 14. Second, the vehicle trajectory-based optimization chose to maintain a 100 second cycle length for the MD time period while the traditional optimization increases it to 120 seconds.

Overall, the vehicle trajectory-based system outperformed the traditional approach, reducing the overall control delay by 17.4% and the number of stops by 20.4%, compared to reductions of 13.7% and 14.9%, respectively, achieved by the traditional optimization. Large improvements in coordination were observed in the AM time period, where the vehicle trajectory-based optimization reduced average delay at each coordinate movement by 4.1 seconds, compared to the 3.5 seconds achieved by the traditional. For the coordinated movements, the vehicle trajectory-based optimization outperformed the traditional in every time period except PM (15-19).

It was unclear if the time period border change chosen by the vehicle trajectory-based optimization from 10 to 9 yielded any superior benefits than the traditional optimization's choice to maintain the time period border at 10. While the coordination seemed to be slightly better (0.1 second), the overall average control delay and number of stop improvements were not as significant as the traditional optimization for hour 9 to 10. These results make sense based on the method used for the timing plan schedule changes, which was based on the travel patterns along the corridor. Future work will develop other methods for timing plan schedule optimization that considers the entire network.

The decision to maintain the 100 second cycle length for the MD time period yielded much better performance than the traditional optimization's increase to 120 seconds. Not only did the vehicle trajectory-based optimization perform 1.1 seconds better in average delay along the coordinated movements, but the average control delay and number of stops per movement dropped by 16.7% and 17.8%, respectively, compared to only 1.2% and 11.5%, respectively, in the traditional optimization. A huge reason for these reductions was the improvement in coordination along a side street, which was made possible by maintaining the 100 second cycle length. These results demonstrate the advantages of using vehicle trajectory data to evaluate the impacts of traffic signal timing across jurisdictions. Projects utilizing this data should optimize signals across jurisdictional boundaries.

The results of this study offer a valuable case study for directly comparing the implementation of two distinct optimization methods. Although the vehicle trajectory-based optimization demonstrated overall superior performance, a single study is insufficient to draw definitive conclusions about which method is categorically better—especially given that the traditional optimization outperformed the vehicle trajectory-based approach during certain time periods. Nonetheless, the findings highlight the promise of using vehicle trajectory data as a practical and effective tool for traffic signal optimization in real-world applications, reducing the costs of these projects by around 35%. In addition, the ability to automatically generate new signal timing plans from this data will allow us to develop new plans on a more iterative time frame in response to evolving traffic patterns.

*Recommendations for Further Research*

The methods presented in this project evaluated strategies for optimizing timing plan schedules, offsets, green splits, and cycle lengths. However, no methods for optimizing traffic signal control by adjusting left turn operations were proposed (permissive/protected and leading/lagging). In these models, many competing factors will need to be considered such as the trade-offs between protected and permissive left-turns and the required designated lane requirements. There is also an opportunity to include the safety considerations of change intervals for left-turn movements. For instance, left turns may require longer yellow change intervals than through movements. However, many intersections control these movements through one phase/signal head. These considerations should be included in future optimization models looking at left-turn operations.

Vehicle trajectory streaming could enable more responsive dynamic control strategies that react to the time-varying traffic conditions. While previous work has explored this possibility in China, future research should investigate the practical issues surrounding implementation of such as a system in the United States (*35*). The temporal-spatial qualities of vehicle trajectory data will allow the signal timing management system to easily identify congestion in the form of split failures caused by oversaturation and spillovers. For instance, cycle failures and spillovers can be easily identified, especially compared to fixed-point detectors. We can locate, with a high level of confidence, congested movements in real-time at an intersection if we observe multiple trajectories exhibiting these characteristics in a short time frame (3-5 minutes). Therefore, future research should develop algorithms for incrementally adjusting the green splits in real-time to alleviate these oversaturated conditions.

Finally, Cellular Vehicle-to-Everything (CV2X) technology has the potential to enable real-time signal control strategies by transmitting vehicle trajectory information through cellular infrastructure. Leveraging this data to develop real-time traffic signal control strategies that remain compatible with existing controllers would be highly beneficial. In traditional systems, physical detection devices send a "call" for service whenever a vehicle is detected. This approach, known as actuated signal control, follows well-established logic implemented in current signal controllers. Future research could implement methods for replicated vehicle actuation to enable more large-scale actuated signal control through real-time vehicle trajectory data. One major challenge would be to provide all vehicles with equal benefits, not just those that are equipped with technology. One potential solution could be based on the probabilistic methods established in Dr. Xingmin Wang's doctoral dissertation (*36*).

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