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FHWA/IN/JTRP-2010/22

Final Report

**QUANTIFYING BENEFITS OF TRAFFIC SIGNAL
RETIMING**

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Final Report

Quantifying Benefits of Traffic Signal Retiming

Introduction

According to the economic theory applied to transportation systems analysis, changes in the level of service of a facility are expected to induce changes in the level of demand. For example, an improvement in the level of service leading to a decrease in user cost should lead to an increase in the demand volume due to the new equilibrium point between the supply and demand curves. It is well known that retiming signal systems has direct benefits for arterial operations. However, it is often difficult to quantify these benefits in terms of user cost reductions and environmental benefits.

This project presents a methodology for measuring and interpreting changes to user costs,

and quantifying changes in demand for vehicle and pedestrian modes. The two technological innovations on which the methodology is based are high-resolution signal event data and probe vehicle travel time measurement with Bluetooth device MAC address matching. Changes in vehicle and pedestrian demand are quantified by measuring vehicle counts and pedestrian phase utilization with real-time data logging. The impact on user costs for the vehicle mode is quantified by changes in the median probe vehicle travel time, which can also be used to estimate the change in user costs and the reduction in carbon emissions.

Findings

This project presents the results from three case studies in which high-resolution signal event data and Bluetooth MAC address matching were used to measure different aspects of the supply and demand model from economic theory.

In the first case study, 21 months of vehicle volume data are used to determine whether demand volumes increased in response to a 1.9-minute decrease in travel time (a 20% decrease) for the Saturday timing plan on SR 37 in Noblesville, Indiana. Vehicle volumes were recorded over 21 months to measure the demand volume. After adjusting for seasonal variation, a slight increase in the demand volume was quantified. The difference was not found to be statistically significantly different, likely because Saturday demand is inelastic with respect to user cost, but the same methodology could be used to test whether an improvement had an impact on demand in other scenarios.

The second case study investigated changes in pedestrian demand related to the implementation of an exclusive pedestrian phase at the intersection of Northwestern Ave. and Stadium Ave. in West Lafayette, Indiana. Using

the percentage of signal cycles featuring actuated pedestrian phases as a proxy measure for the number of pedestrians, changes in demand for pedestrian service were tracked over 18 months. The effects of seasonal variation, special events, weather, and the signal timing plan were quantified. To determine how the relative effects of numerous variables co-influenced the level of pedestrian phase utilization, a Tobit model was estimated. The implementation of the pedestrian phase was found to lead to a 9% increase in the utilization of the pedestrian phase, which is attributed to an increase in crossings at the intersection as opposed to midblock crossings. Another interesting finding from this case study relates to weather conditions; the positive coefficient for the variable related to snowfall corresponds to increased pedestrian activity at the intersection due to the fact that midblock crossings become difficult due to the blocking of pedestrian paths by snow banks. Although none of these findings are surprising, this methodology demonstrates that quantitative values of the relative impact of the different variables can be determined using high resolution event data.

The third case study returns to the vehicle mode and considers the impact of travel time improvements from a second signal offset optimization study on SR 37. The travel time data was used to quantify the user impact of the changes in travel time under alternative optimization objectives. Based on the change in median travel times, a lower bound on the estimated annual user cost savings was estimated

at \$472,817 with an associated reduction in CO₂ emissions of 197 tons per year. These benefits were obtained from the optimization of the Saturday timing plan, and quantify the potential benefits to be gained from signal optimization. Additionally, changes in arterial travel time reliability are also quantified by decreases in the difference between the 25th and 75th percentile travel times.

Implementation

INDOT is currently deploying widespread implementation of high-resolution signal event data and probe vehicle travel time. The increased use of these measurement tools in the state of Indiana means that it will soon be possible for engineers to measure the impact of signal maintenance activities in terms of the change in

arterial travel times, user costs, and environmental impact. Additionally, changes in demand that are induced by signal retiming can be directly quantified using vehicle counts per the high resolution signal event data. These capabilities will benefit the agency by making it possible to more concretely justify investment in signal operations..

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16. Abstract Improvements in the quality of service on a signalized intersection or arterial can be interpreted as a reduction in the user cost of service, which is expected to induce demand based on economic theory. This report presents a methodology for measuring and interpreting changes to user costs, and determining whether demand was induced. High-resolution signal event data and Bluetooth device MAC address matching are demonstrated in three case studies with the purpose of quantifying the impacts of changes in signal timing plans. In the first case study, 21 months of vehicle volume data are used to test whether demand was induced by optimizing offsets on a Saturday plan. In the second case study, the increase in demand for pedestrian service is quantified with respect to the implementation of an exclusive pedestrian phase using an econometric model taking the effects of season, weather, and special events into account. Finally, the third case study demonstrates the use of vehicle travel time data in quantifying changes in user costs and environmental impact (tons of carbon). A method of describing changes in travel time reliability is also presented.			
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ABSTRACT

Improvements in the quality of service on a signalized intersection or arterial can be interpreted as a reduction in the user cost of service, which is expected to induce demand based on economic theory. This report presents a methodology for measuring and interpreting changes to user costs, and determining whether demand was induced. High-resolution signal event data and Bluetooth device MAC address matching are demonstrated in three case studies with the purpose of quantifying the impacts of changes in signal timing plans. In the first case study, 21 months of vehicle volume data are used to test whether demand was induced by optimizing offsets on a Saturday plan. In the second case study, the increase in demand for pedestrian service is quantified with respect to the implementation of an exclusive pedestrian phase using an econometric model taking the effects of season, weather, and special events into account. Finally, the third case study demonstrates the use of vehicle travel time data in quantifying changes in user costs and environmental impact (tons of carbon). A method of describing changes in travel time reliability is also presented.

CHAPTER 1. INTRODUCTION

1.1. Study Objective and Summary

The objective of this study is to develop procedures that leverage existing INDOT infrastructure to develop a series of analysis procedures to quantify the benefits of retiming traffic signal systems. This report documents three case studies that demonstrate the application of several methodologies for assembling the necessary elements of an analysis of the impacts of changes to signal timing plans. Specifically, methods for measuring vehicle and relative pedestrian demand over long time periods are discussed, and methods of analyzing the impact of signal timing plan changes are demonstrated.

The two technological solutions that this report use are high-resolution traffic signal event data and Bluetooth device MAC address matching. In summary, the data logging capabilities of recently developed new traffic signal controllers can be used to facilitate the long-term characterization of vehicle counts and other signal performance characteristics. Travel time measurement by Bluetooth device MAC address matching yields a much larger and more extensive set of data points than both traditional and GPS-assisted floating car studies. This report demonstrates the use of high-resolution vehicle signal event data to measure changes in vehicle and pedestrian demand over time. Measured travel times are used to quantify changes in the central tendency and reliability of travel time on an arterial, from which the user benefits and environmental impacts are extrapolated.

1.2. Motivation for Study

The operation of traffic signal timing plans can be envisioned as a series of feedback loops defined by a *design* process and a *maintenance* process, as illustrated by Figure 1.1. Once the agency objectives and priorities have been defined (Task I), data collection activities are conducted (Task II) to characterize the design volumes and other characteristics for a particular signal system. The design process consists of Tasks III and IV, which are linked by a feedback loop (“FB1”). Although varying by agency and by the importance of the project, the timing plan design process involves several iterations between software modeling and design and documentation of timing plans. During this exercise, it is possible to obtain precise performance measures based on traffic simulation

or other software analyses. The quality of this information is limited by the accuracy of the analysis procedure and by the quality of the data. Because the cost of obtaining data over extensive time periods is prohibitive, both design and timing plan analysis are typically not well characterized for all time periods affected by a signal timing plan.

Once the timing plans have been finalized, the next stage is the maintenance process, which involves another feedback loop (“FB2”). In this case, the timing plans are deployed (Task V) and, ideally, are evaluated (Task VI). If during the evaluation problems are identified, this would lead to modification of the timing plan and additional iterations of the process. In practice, extensive evaluation of timing plans as they operate is not typically carried out because of the expense of obtaining field data without automated monitoring procedures. Often, action is warranted by public feedback (complaint calls). Even if agencies do expend the effort to evaluate and retime systems regularly, there is a lack of tools for measuring the impact of those efforts. The most extensively used procedure is the floating-car study, which like all manual data collection methods is expensive and can only provide information about a limited portion of the entire range of time periods during which the signal operates. It is desirable, therefore, to develop methods to narrow this gap in the second feedback loop. The methods in this report are intended to assist in the documentation of procedures in the maintenance feedback loop.

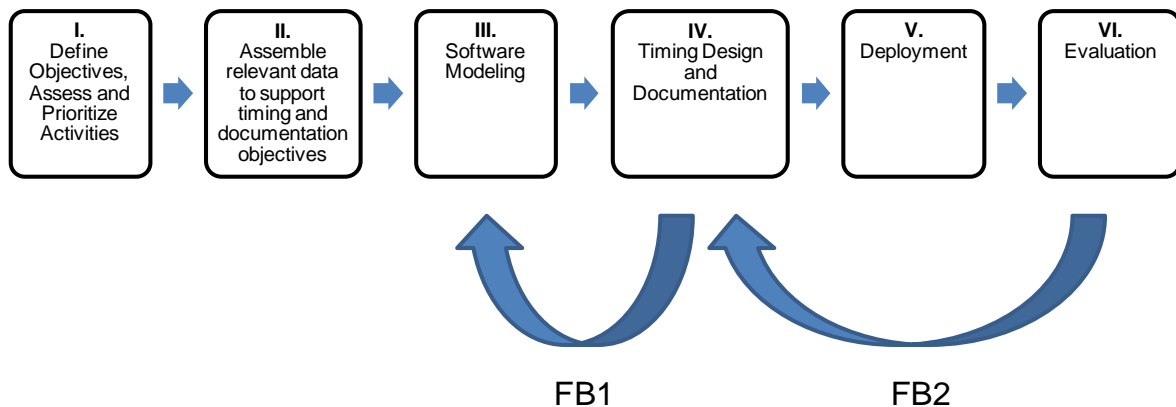


Figure 1.1 Procedural steps and feedback (FB) loops in traffic signal systems operations.

1.3. Organization of the Report

As discussed in this chapter, it is desirable to quantify the user benefits resulting from signal retiming activities. This report demonstrates the use of two new tools for performing that quantification: high-resolution signal event data and travel time measurement using Bluetooth device MAC address matching. This report presents three case studies of timing plan changes affecting vehicle and pedestrian modes. The case studies are organized into three chapters that correspond to the three technical papers in which the results were disseminated throughout the course of the project (1,2,3).

In Chapter 2, we analyze the changes in traffic volumes over a 21-month observation period to investigate whether it is possible to measure any change in demand resulting from a 1.9-minute improvement in travel times. Traffic counts are corrected for seasonal variation, and used to identify a 2.6% increase in the volume. While a *t*-test of the daily traffic volumes from before and after the signal timing plan change does not reveal that the impact was statistically significant due to the inelasticity of demand during the affected time of day, the methods used in this chapter could be applied to other scenarios and demonstrate the effectiveness of combining high-resolution signal event data and measured travel times.

In Chapter 3, we examine the implementation of an exclusive pedestrian phase at an fully actuated urban intersection. The percentage of signal cycles with actuated pedestrian phases is proposed as a proxy measure of demand for pedestrian service. High-resolution signal event data were collected over an 18-month time span. The effects of daily/weekly/annual variations, special events, weather (temperature and precipitation), seasonal changes in activity patterns, and changes in pedestrian signal phasing are documented. A Tobit model is used to account for the influences of these variables and understand how they co-influence pedestrian activity. The implementation of an exclusive pedestrian phase is associated with a 9% increase in pedestrian phase utilization at the intersection. This change is associated with a decrease in user cost relative to performing midblock crossings. The modeled impact of snowfall events adds further insight by showing that as the user cost of making midblock crossings increases, pedestrian activity at the intersection increases.

Chapter 4 presents outcomes from an arterial offset optimization study conducted on an eight-mile arterial in which several alternative optimization objective functions were evaluated. The study consisted of a one-week base data collection, and four one-week

deployments of offset plans developed using four alternative optimization objective functions. Probe vehicle data was collected during the study period to evaluate the impacts of the alternative optimization functions on corridor travel time. All of the objective functions were successful in significantly reducing median corridor travel time. Median travel time decreased by more than one minute in both directions over the 8-mile corridor, and travel time reliability was improved, as quantified by a reduction in the difference between 75th and 25th percentile travel times. A lower bound on the estimated annual user cost savings was estimated at \$472,817 with an associated reduction in CO₂ emissions of 197 tons per year.

CHAPTER 2. EVALUATION OF VEHICULAR DEMAND ELASTICITY

2.1. Introduction

Improvements in service in transportation systems lead to an increase in utilization of the service. It is expected that this change in demand would be reflected in changes to observable events such as vehicle detections on an arterial. As discussed in Chapter 1, one objective of this project was to characterize shifts in demand due to timing plan changes. In this chapter, we discuss the results of measurements of traffic volumes over a 21-month time period during which a change to signal offsets was implemented that improved the travel time by nearly 2 minutes.

2.2. Offset Improvement Study

In July 2009, a signal offset retiming study on SR 37 in Noblesville, Indiana was carried out (4). A map of the SR 37 corridor is shown in Figure 2.1. This arterial links the city of Indianapolis to smaller communities to the north and is thus a commuter route with recurring tidal flows throughout the week. On weekends, traffic demand is still rather high but is more evenly spread out throughout the day. A single time-of-day (TOD) plan is used for the entire day on Saturday (spanning 0600-2200). Prior to this study, the performance of the Saturday timing plan had not been thoroughly evaluated; the initial plan had been designed to a high degree based on engineering judgment, there having been no manual counts from Saturdays, little field validation, and no public feedback regarding the weekend plans. As is common in signal operations, because of the dearth of available information on signal operation, lower priority time periods such as weekend plans often contain opportunities for system improvement.

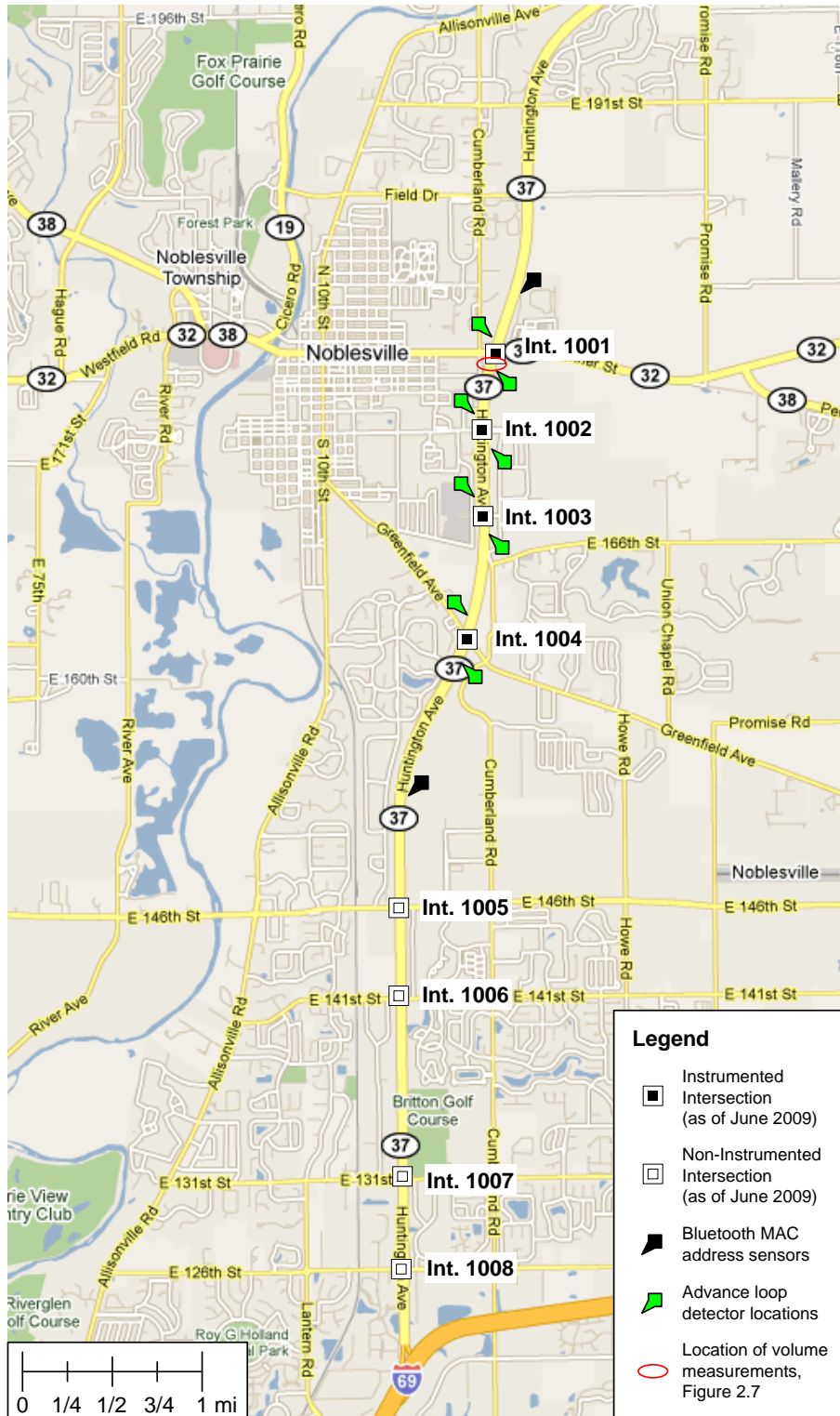


Figure 2.1 Map of SR 37 corridor showing equipment locations during the 2009 study.

The segment spanning Int. 1004 and Int. 1001 (see Figure 2.1) was instrumented with signal controllers capable of logging high-resolution event data. This data was used to optimize the offsets as follows. In the course of that research study, a graphic tool called the “Purdue Coordination Diagram” (PCD) was developed to visualize and evaluate the quality of progression by superimposing vehicle arrivals on top of the occurrence of green bands. An example PCD is shown in Figure 2.2. The horizontal axis of the diagram is the time of day, while the vertical axis is the time in cycle. Vehicle arrivals are indicated by dots, while various signal events are reflected by lines as indicated in the figure. The most important line is the beginning of green; the vehicles plotted above this line are those that arrived during green, while those plotted below the line arrived during the preceding red phase. The clustering of dots/vehicles in this plot is indicative of platoons. In Figure 2.2, primary (“i”) and secondary (“ii”) platoons are visible, indicating the through movement and side street turning movements feeding into the link at the upstream intersection. The PCD is coupled with a quantitative performance measure, the percent on green (POG). The impact of offset adjustments can be modeled by shifting the vehicle arrivals at the affected coordinated lane groups, with the magnitude of the adjustments directly related to the changes in offsets (both at the local and upstream intersections). The resulting changes to POG can be used to optimize offsets.

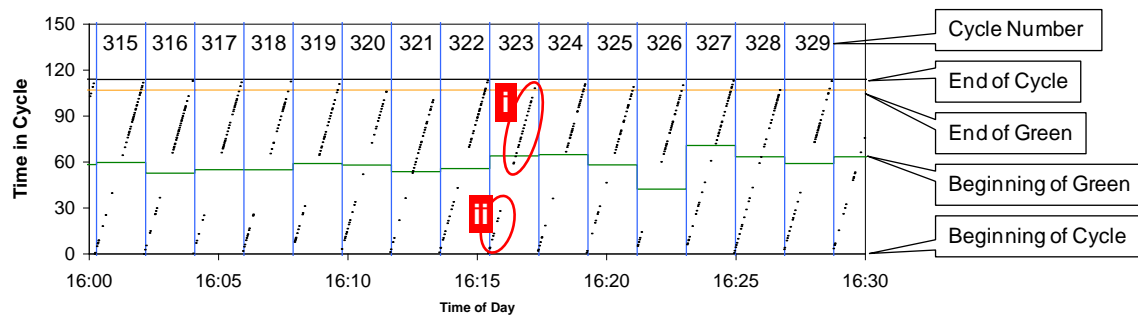


Figure 2.2 Explanation of the Purdue Coordination Diagram (PCD).

Based on the PCD and the above described model for predicting traffic patterns, new offsets were developed for the Saturday plan that achieved a substantial improvement in POG for most of the coordinated through movements. The new offsets were implemented in the field on July 18, 2009. The observed PCDs for the eight coordinated through movements on the instrumented section of SR 37 are shown in Figure 2.3 and Figure 2.4 respectively for the “before” scenario (old offsets) and the “after” scenario (new offsets). Changes in signal operations can be observed in the figures as follows:

- Northbound platoons at Int. 1002 had been arriving in red (Figure 2.3, “a”), and therefore were likely to be stopped. After the offset adjustments, the platoons mostly arrived during green (Figure 2.4, “a”).
- Both northbound and southbound vehicles at Int. 1004 were not being captured well by the green phase. Northbound vehicles were arriving in red (Figure 2.3, “b”) and southbound vehicles were arriving slightly before red (Figure 2.3, “c”). Offset adjustments were able to capture both sets of platoons in green (Figure 2.4, “b” and “c”).
- Because the upstream intersection was not coordinated, southbound arrivals at Int. 1001 were random, as shown by the absence of platoons in the PCDs (Figure 2.3 and Figure 2.4, “d”); there was no impact from offset adjustments.
- Due to performance tradeoffs between coordinated movements on two ends of a link, it was not possible to perfectly capture all coordinated platoons in green. The northbound platoons at Int. 1001 (Figure 2.4, “e”) arrived slightly before green, while a portion of the southbound platoons at Int. 1003 (Figure 2.4, “f”) were cut off by the end of green.
- Several minutes of missing data due to equipment downtime is visible in Figure 2.4 (“z”).

For additional details on the offset optimization procedure, the reader is referred to the 2010 TRB paper (4).

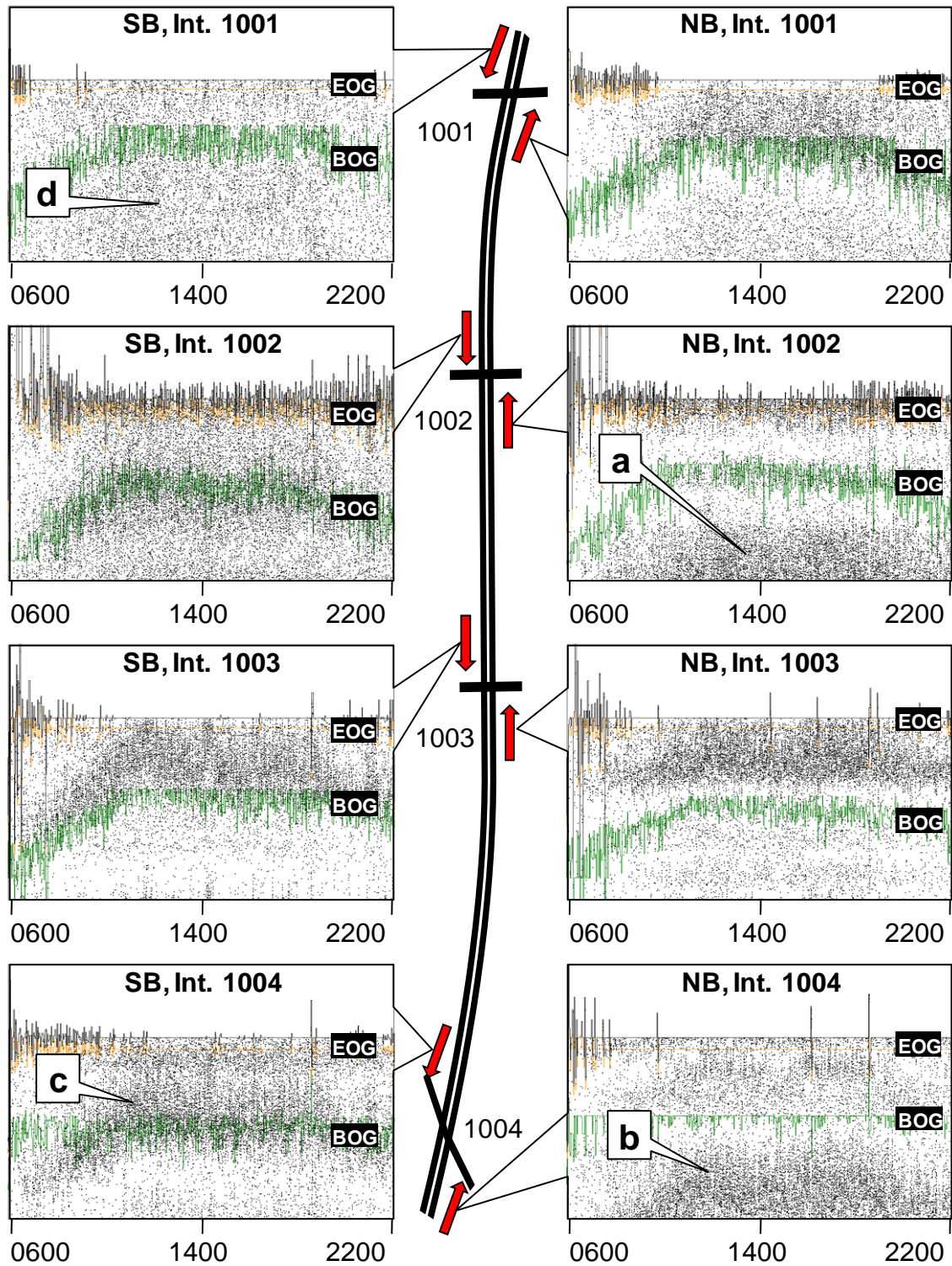


Figure 2.3 SR 37 PCDs before adjustment (June 6, 2009).

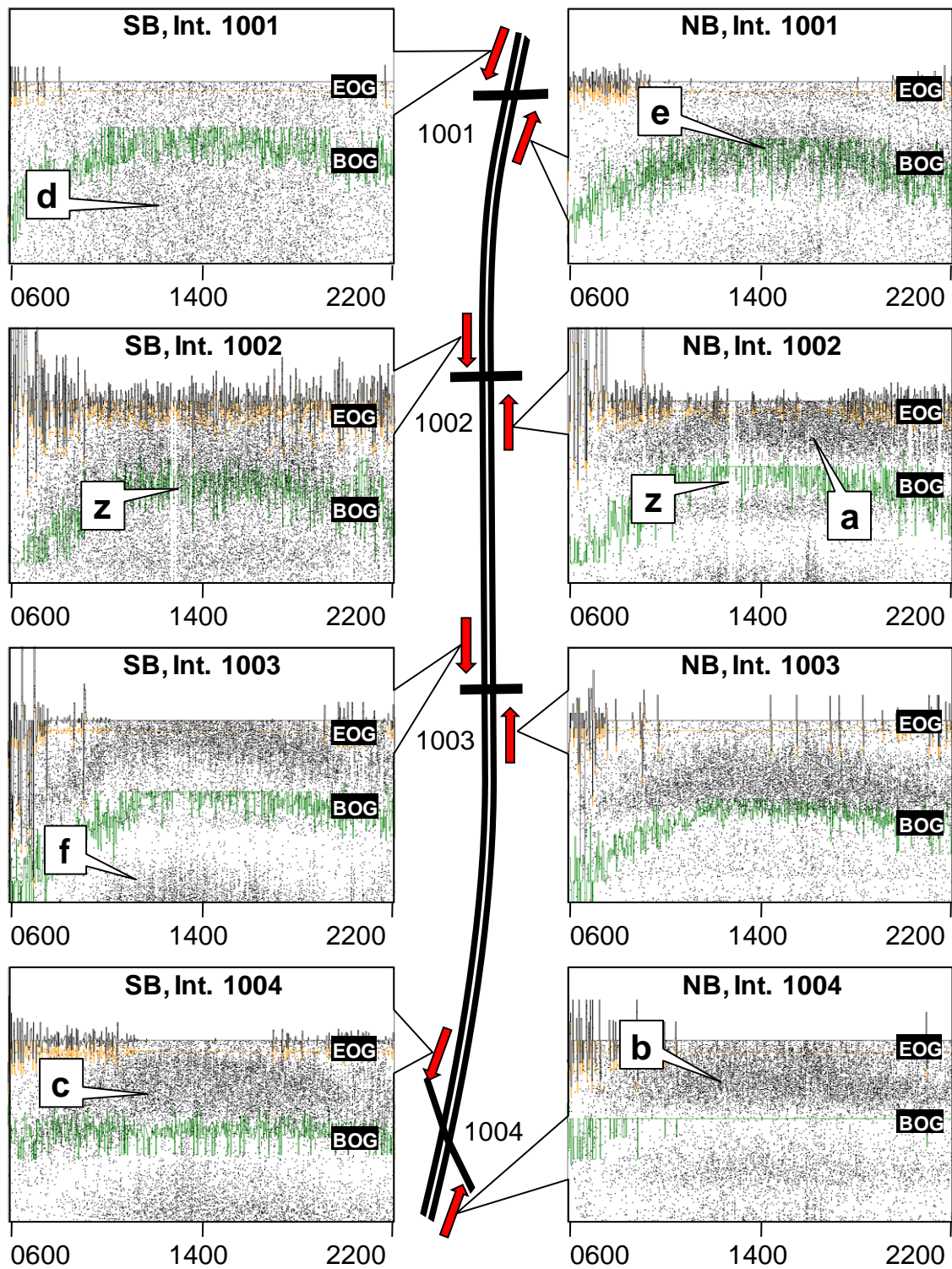


Figure 2.4 SR 37 PCDs after adjustment (July 25, 2009).

2.3. Measurement of User Benefits: Travel Time Impact

In addition to measuring the impact on signal performance by means of the PCD, travel times were concurrently measured in the study using Bluetooth device MAC address matching. Temporary MAC address sensors were installed at midblock locations throughout the corridor (see Figure 2.1). Northbound and southbound travel times on SR 37 were characterized by matching MAC detected at the endpoint sensors. For example, if the same MAC address was recorded just north of Int. 1001 at 9:00:00 and just south of Int. 1004 at 9:03:00, a vehicle travel time of 3 minutes in the southbound direction would be recorded. Figure 2.5 shows cumulative frequency diagrams of travel time before and after the offset adjustment, with northbound and southbound operations illustrated respectively by Figure 2.5a and Figure 2.5b. The median northbound travel time decreased by 1.9 minutes, while the median southbound travel time improved by 0.5 minutes.

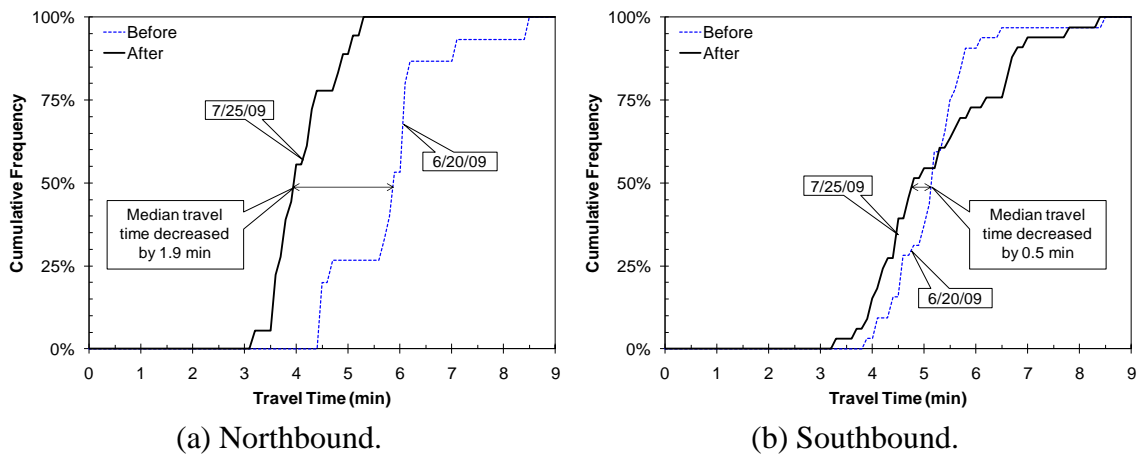


Figure 2.5 Observed changes in SR 37 travel time due to adjustment of offsets.

2.4. Characterizing Changes in Demand

Figure 2.6 shows a diagram that summarizes the economic theory on transportation supply and demand. The two price-volume curves for “System A” and “System B” represent the system performance before and after the offset change. System B, notably, has a lower price (or user cost) per unit volume because of the improvement in service. The demand curve represents the user response to the supply, which in this case is illustrated as increasing as the system improves, or its price-volume curve moves to the right. Another concept associated with this type of analysis is that of *elasticity*. The price elasticity of demand would be defined as the percentage change in volume that results from a 1% change in the price, and is associated with the slope of the demand curve in Figure 2.6.

To determine whether the 1.9-minute decrease in Saturday northbound travel time induced an increase in volume, Saturday northbound vehicle counts from over 21-months spanning September 2008 and May 2010 were compiled. Northbound daily traffic was measured by stop bar count detection at all northbound movements at Int. 1001 (see Figure 2.1). Figure 2.7a shows the northbound Saturday daily traffic for the analysis period. The dashed line in the center of the plot divides the timeline into two regions, before and after the offset adjustment. Approximately 10 months of data were tracked before and after the adjustment. The plot does not indicate any clear evidence for changes in demand volumes that might have been induced by the improved travel time. Rather, seasonal variations appear to dominate the trend, with volumes peaking in the warm weather months, and bottoming out in winter. There does not appear to be any increase in volume in the weeks immediately following the implementation of the change.

The impact of seasonal variation can be corrected by multiplying the daily traffic measurements by seasonal adjustment factors¹. At the moment, only seasonal factors through December 2009 are available, so we approximated by applying the 2009 factors to the 2010 data. Figure 2.7b shows a plot of this data after the adjustments to the volumes are made. Compared to the unadjusted volumes in Figure 2.7a, the seasonal variations have largely vanished from the graph. There is a slight increase in the number of vehicles throughout the study period, but it is difficult to observe because of the considerable stochastic variation from week to week.

¹ http://www.in.gov/indot/files/INDOT_2009_AADT_Adjustment_Factors.pdf

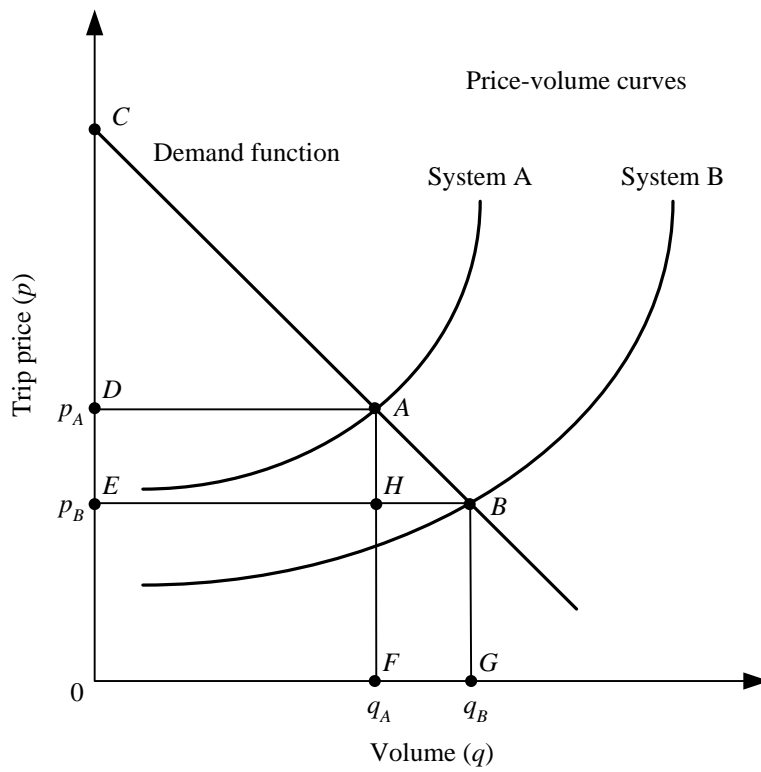
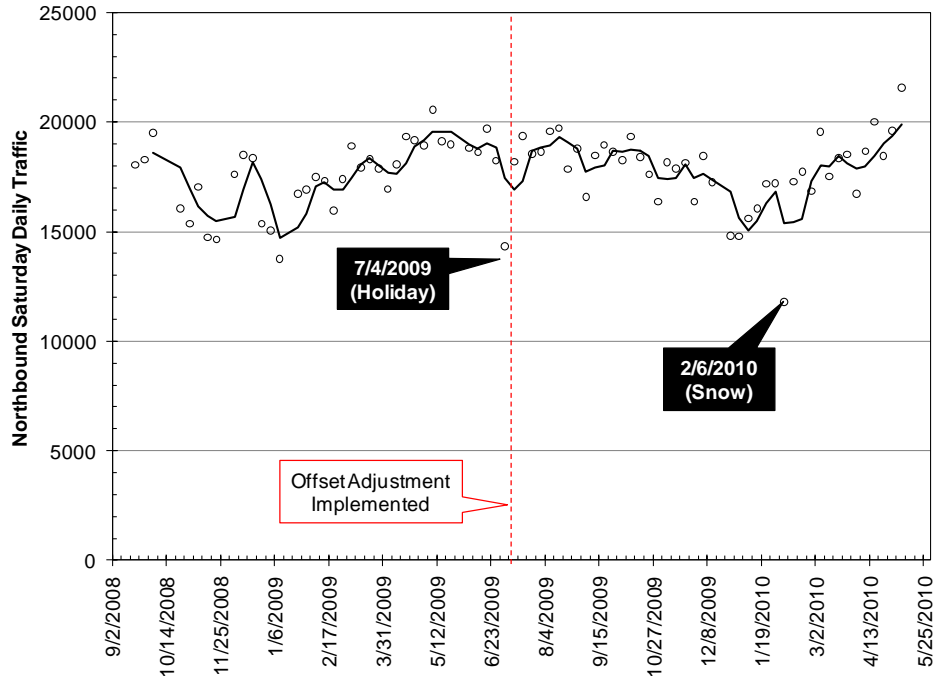
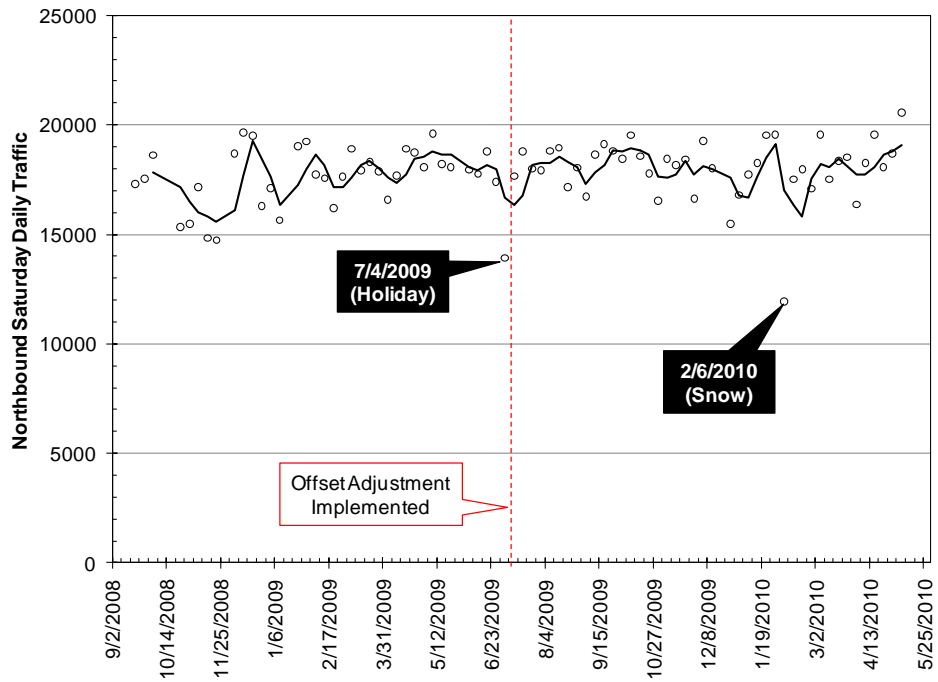


Figure 2.6 Economic concepts associated with changes in service in a transportation system, after Wohl and Hendrickson (5).



(a) Actual vehicle counts.



(b) Corrected for seasonal variation.

Figure 2.7 Northbound Saturday daily traffic at SR 32/SR 37 (Noblesville, IN).

To determine the magnitude and significance of the change in the number of vehicles, we conducted a *t*-test between the seasonally-adjusted volumes before and after the offset optimization study. First, we eliminate the two outliers with unusually low volumes that occurred on to July 4, 2009 (a public holiday) and February 6, 2010 (a snow event). Next, we assemble the 36 remaining “before” and 29 “after” seasonally-adjusted Saturday volumes and perform the *t*-test. The results of the test are shown in Table 2.1. The average daily traffic volume increased by 464 (difference in means), corresponding to an increase of 2.6%. The results of the *t*-test indicate yield a *P*-value of 0.123, which indicates that the difference in volumes would not be considered statistically significant at a confidence level above 88%. This does not infer that there was no effect at all (6), but rather it finds that we cannot reject (at typical confidence levels of 90% or 95%) the hypothesis that the effect is due to randomness.

This minor change in traffic volumes implies that the demand function associated with northbound Saturday volumes on SR 37 is inelastic to cost, at least within the range of improvement of 1.9 minutes. This is perhaps not unexpected, because it does represent a time period in which motorists would be less sensitive to a two-minute travel time change, as compared to a weekday morning, for example. Although this finding is perhaps not as compelling as more clear evidence of induced demand, the above described methods could be used to detect it in such a situation.

Table 2.1 Statistical comparison of before and after Saturday volumes
(corrected for seasonal variation).

	Before data: 9/20/2008–6/27/2009	After data: 7/11/2009–1/30/2010
Number of Saturdays	36	29
Mean daily traffic	17670	18133
Standard Deviation	1321	1004
Difference in Means		464
Percentage Change		2.6%
<i>t</i> -value		1.5609
<i>P</i> -value		0.1235

2.5. Conclusion

For daily traffic counts collected over a long time period, the analyst has the advantage of having tables of seasonal correction factors and yearly growth factors that can readily be applied to the data. Comparing Figure 2.7a to Figure 2.7b reveals the effectiveness of these factors in reducing the effects of seasonal variation. The effect of the operational change were found by taking the difference in the means. In this case, the difference in the means could not be said to be statistically significant, meaning that the possibility that the change is due to random variation cannot be ruled out. From this, we conclude that the change in performance did not yield a discernable effect on the demand volume for Saturdays. From this, we infer that demand on Saturdays is inelastic to changes in the system performance of the kinds that are possible from signal timing. If the study were repeated for a time period in which demand was more elastic, such as during peak period commute times on weekdays, a significant effect might be observable. Regardless of the findings of this particular study, however, the methods described here could be used to analyze the economic impacts for time periods where demands are expected to be elastic with respect to the service level resulting from signal timing.

CHAPTER 3. EVALUATION OF PEDESTRIAN DEMAND ELASTICITY

3.1. Introduction

There is a need for more and higher quality data on pedestrian demand patterns for a number of applications in planning, transportation engineering, public health, and other areas. It is particularly desirable to better characterize the influence of daily, weekly, and annual variations; the impact of weather and special events; and the effects of changes in pedestrian phasing.

The proportion of traffic signal cycles in which pedestrian phases are actuated is proposed as a surrogate measure of pedestrian volumes. Although this measure does not directly quantify the number of pedestrians using the facility, it allows the relative demand between different time periods and operating conditions to be characterized. Most importantly, the methodology can be implemented at thousands of intersections where pedestrian-actuated phases are in operation with minimal cost.

A case study is presented where pedestrian phase utilization was tracked between November 2008 through April 2010 at a signalized intersection. Changes in the level of pedestrian activity are characterized with respect to daily, weekly, and annual fluctuations; weather conditions (temperature and precipitation); special events; changes in activity patterns due to the academic calendar of a nearby university; and changes in pedestrian service at the intersection (implementation of an exclusive pedestrian phase). The impact of these factors are reported in detail and further investigated in an econometric model to reveal insights as to how they co-influence the level of pedestrian activity.

3.2. Characterizing Pedestrian Demand

More and better data on pedestrian utilization is needed for planning, safety, and operations applications in transportation engineering, as well as other areas (e.g. public health). At present, methods for developing pedestrian volumes lag behind the corresponding methods for vehicular traffic (9). Models are emerging for predicting demand for pedestrian facilities from surrounding land use (e.g., 10, 11, 12), which may eventually lead to planning analysis tools similar to vehicle trip generation tables. There

are few studies on the smaller-scale aspects of pedestrian travel, such as how pedestrian activity varies on a day-to-day basis and with respect to weather, special events, and other factors. While planners currently have access to published seasonal adjustment factors for vehicle traffic, similar numbers are not well characterized for pedestrians at most locations. There is a growing awareness of this disparity as communities continue to become more aware of the importance of non-motorized modes. However, agencies face substantial challenges in obtaining this data.

Perhaps the most substantial challenge to collecting data on pedestrian activity is finding the resources necessary to collect the data. There are emerging technologies for automatic pedestrian counting methods (13,14,15,16,17,18,19) and a desire to develop traffic signal performance measures that characterize pedestrian service (7,21). However, most agencies continue to rely on manual pedestrian counts to characterize pedestrian activity in an area (13). Two recent studies have proposed methodologies that could potentially characterize pedestrian demand effectively over a broad region over an extended time period, particularly if the concepts are combined. Scheider *et al.* (16) proposed a methodology for using automatic pedestrian counts to extrapolate volumes from two-hour manual counts to a weekly basis. Estimated volumes could further be transferred to locations with similar land use characteristics or form the basis of safety analyses. Aultman-Hall *et al.* (19) presented the results of automatic pedestrian counts after one year of data collection, permitting the observation of fluctuations with respect to seasonal variations and weather. Combining long-term measurement of variations in pedestrian demand using automatic data collection methods with short-term, high-precision manual counts could form a basis for characterizing pedestrian demand in a large geographic region throughout the year, closing the disparity in planning and engineering resources for vehicle traffic and pedestrian traffic.

The methodology presented in this chapter could accelerate that process by observing relative changes in pedestrian demand over a long time period using a surrogate measure, the percentage of traffic signal cycles where pedestrian phases are actuated. We envision that this would be combined with short-term manual counts, or by automatic counts (perhaps by equipment that is rotated throughout numerous locations in a jurisdiction) to characterize pedestrian demand for many different conditions.

This methodology has the advantage of being almost immediately deployable at thousands of intersections where pedestrian push buttons are in use. The disadvantages of this methodology are that it does not directly provide pedestrian counts, and it is not applicable to locations where pedestrian phases are not actuated.

3.3. Study Location

The intersection of Northwestern Ave. (US 231) and Stadium Ave. in West Lafayette, Indiana is situated on the northwestern edge of the Purdue University campus. This location experiences many different levels of pedestrian demand, while experiencing moderate to high amounts of vehicular traffic. A map of the intersection is shown in Figure 3.1. Academic buildings dominate the southwest quadrant of the intersection, while athletic facilities exist to the northwest. There are several businesses on the northeast and southeast quadrant near the intersection, while the rest of the nearby area is residential. Several important pedestrian traffic flow patterns occur at this location:

- Students and university employees cross from residential areas on the east side of the street to the campus on the west side of the street. This includes both residents of those neighborhoods as well as commuters using street parking.
- At the middle of the day (lunch hour), many pedestrians cross Northwestern Avenue to visit restaurants and other businesses on the east side of the street.
- The number of pedestrians during summer break is much less than during the academic year due to drastic changes in activity patterns. Approximately 40,000 students attend Purdue University, the majority of which do not attend classes in summer.
- During special events, large numbers of pedestrians cross Northwestern Avenue to attend football and basketball games after parking in the neighborhood or at the parking garage on Northwestern Avenue. According to a Purdue University Police Department 2009 report, average attendance for the 2008-2009 academic year was 75,000 people including tailgaters for football games, and 12,500 people for basketball games.

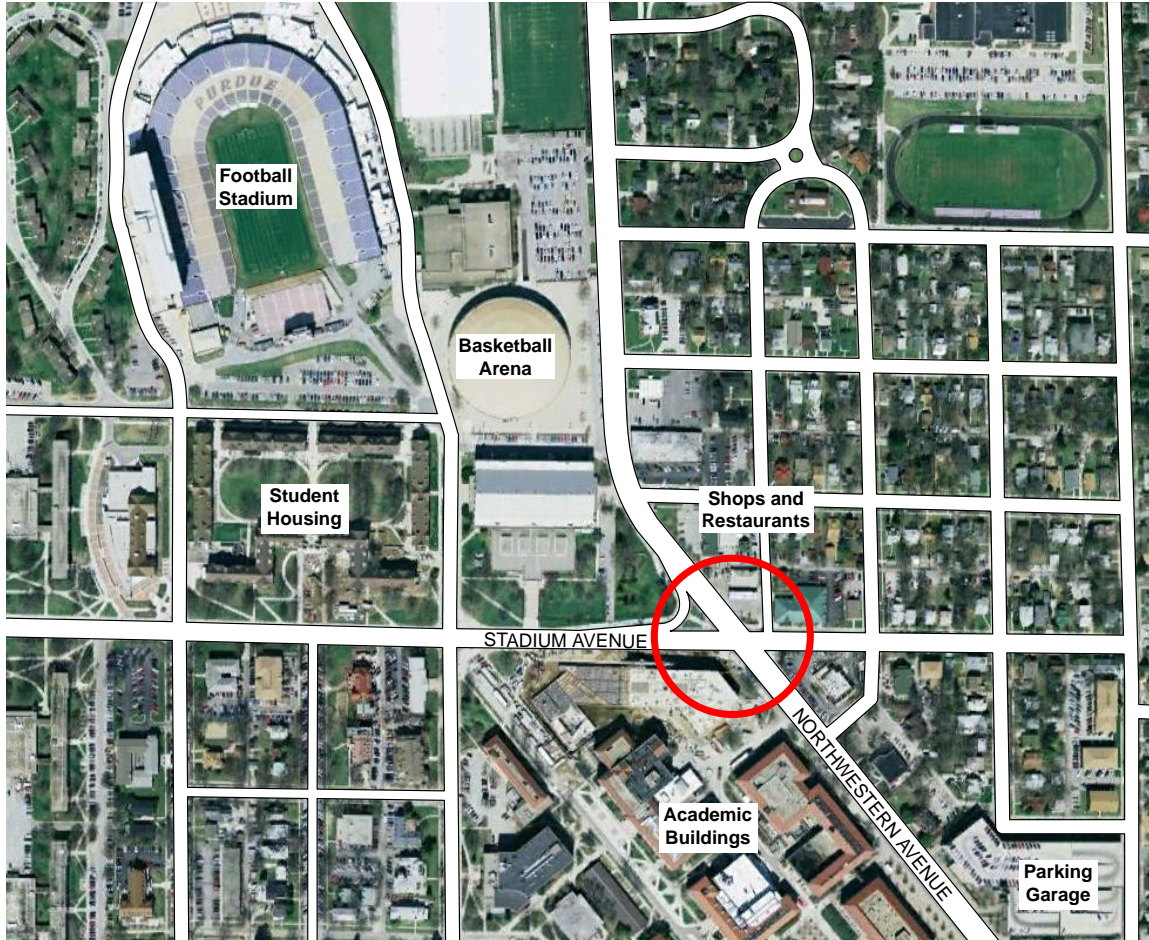


Figure 3.1 Location of Northwestern and Stadium (West Lafayette, IN) and surrounding features (aerial photo source: Google Earth).

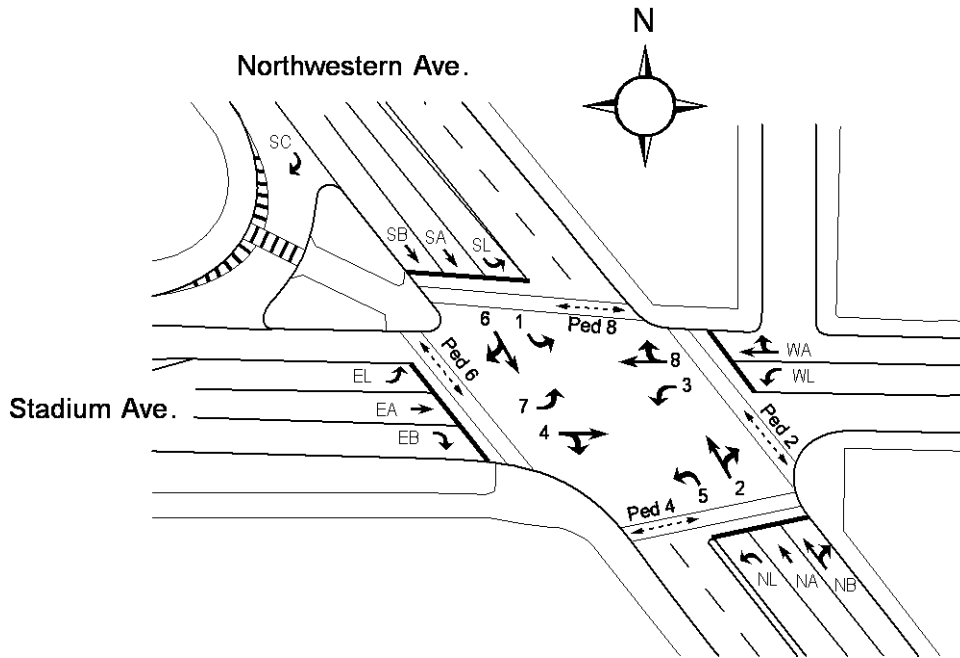
The magnitude of the change in activity patterns during summer can be quantified by changes in the ridership of a bus route that exclusively serves West Lafayette and passes through the test intersection. The average number of riders for this route for January–April 2009 was 19,075 per month, compared to 8,203 per month for May–July 2009, which is a 57% reduction [numbers are for Route 5 (22)].

West Lafayette, Indiana experiences a variety of weather conditions throughout the year. Temperatures range from an average high of 86 °F in July to an average low of 18.5 °F in January. About 41 inches of precipitation fall during the year, with about 27 inches of snowfall on average (23).

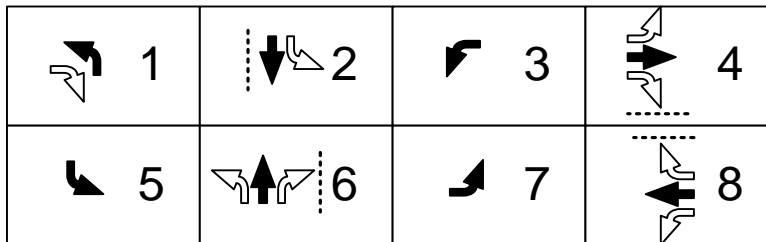
The focus of this report is on impacts of signal timing. In this chapter, we investigate the user impacts of signal timing with regard to pedestrian service. Figure 3.2 describes the intersection of Northwestern and Stadium in detail. The layout of lanes and signal phases are shown in Figure 3.2a. Ring diagrams explaining the signal operation are shown in Figure 3.2b for traditional pedestrian phases and in Figure 3.2c for an exclusive pedestrian phase (pedestrian scramble). These diagrams display the sequence of phases during each signal cycle and the phase numbering scheme in use at the intersection.

Pedestrians crossing Northwestern must traverse five lanes of vehicular traffic. The “Ped 4” movement (*i.e.*, the movement adjacent to vehicular phase 4) is a concern at this intersection because eastbound right turning vehicles often fail to yield to pedestrians. The high volume of vehicles that execute the eastbound right turn during green implies headways that are unlikely to allow comfortable pedestrian movements (7, 21). In 2009, it was decided to add an exclusive pedestrian phase to this movement to improve conditions. This exclusive pedestrian phase is nonstandard, because it is actuated only when pedestrians push the button to cross Northwestern (Ped 4 or Ped 8). If pedestrians request only movements crossing Stadium, they receive only the standard pedestrian indications that time concurrently with the adjacent vehicular phase (Ped 2 or Ped 6).

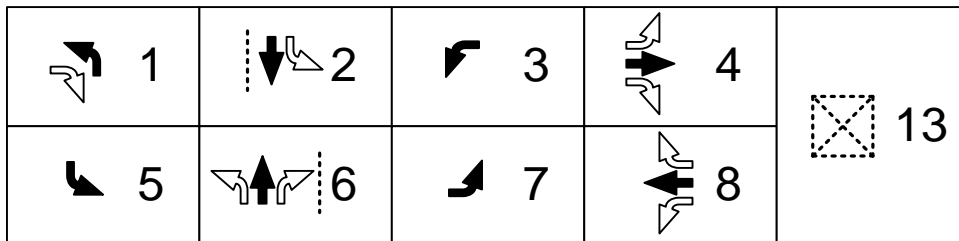
Crossing of Northwestern Avenue is by no means limited to the intersection. It is also very common for pedestrians to cross the street south of the intersection. First, pedestrians negotiate one direction of vehicular traffic, and then stand at the median strip to wait for a safe gap to cross the other direction. It was speculated that the addition of the exclusive pedestrian phase would attract more pedestrians to the intersection to cross Northwestern because of the enhanced convenience of being able to cross both streets and all vehicle movements in one maneuver.



(a) Vehicle and pedestrian phase numbering scheme.



(b) Ring diagram with conventional adjacent pedestrian phases.



(c) Ring diagram with exclusive pedestrian phase.

Figure 3.2 Intersection phase configuration at Northwestern and Stadium.

3.4. Data Collection Methodology

Data was collected at the intersection throughout several intervals spanning November 2008 to April 2010. A log-capable traffic signal controller (24) was used to record the timestamped start and end time of all vehicular and pedestrian phases. Log files were collected via automatic scheduled FTP downloads through a virtual private network (VPN) connection. At this location, a direct fiber optic connection existed between the intersection and the Purdue traffic lab. However, the same signal data logging methodology has been used extensively at numerous remote locations with connectivity established using commercial IP data connections. The cost of implementing similar data collection capability at a typical intersection is summarized in Table 3.1.

Signal cycles were identified from the signal event data using the phase 2 end of green event. This is effective because the intersection operates in fully actuated mode (e.g., there is not a fixed cycle length) and is set to recall to phases 2 and 6. Using these events to divide the timeline into discrete cycles, it was possible to identify the cycles where pedestrian phases took place. For this study, we focused on the pedestrian phases that crossed Northwestern Avenue: Ped 4 / Ped 8, or the exclusive pedestrian phase. The reason for doing so was to observe the impact of implementing the exclusive pedestrian phase. The Ped 4 movement is the most challenging for pedestrians and was the motivation for considering the exclusive pedestrian phase.

In addition to the signal data, weather conditions were obtained from a public database for the nearest geographic location (West Lafayette airport), while the academic calendar and football/basketball game schedule information was obtained from Purdue University's website. All of this data was compiled on an hour-by-hour basis for further analysis. A total of 10,478 data points were obtained. These are summarized in Table 3.2.

Table 3.1 Cost of implementation of the data collection methodology.

Item	Cost
One Time Costs	
Traffic Signal Controller with High Resolution Logging (<i>e.g.</i> , Econolite ASC/3, Peek ATC)	\$2000
Wireless Modem	\$500
VPN Router	\$120
Installation labor (2 hours at \$100 per hour)	\$200
VPN Server	\$200
Dedicated computer for automatic downloads	\$1000
Software for executing automatic downloads	\$100
Total of One-Time Costs	\$4,120
Annual Costs	
12 months of data-only wireless service	\$500/year

Table 3.2 Characteristics of the collected data.

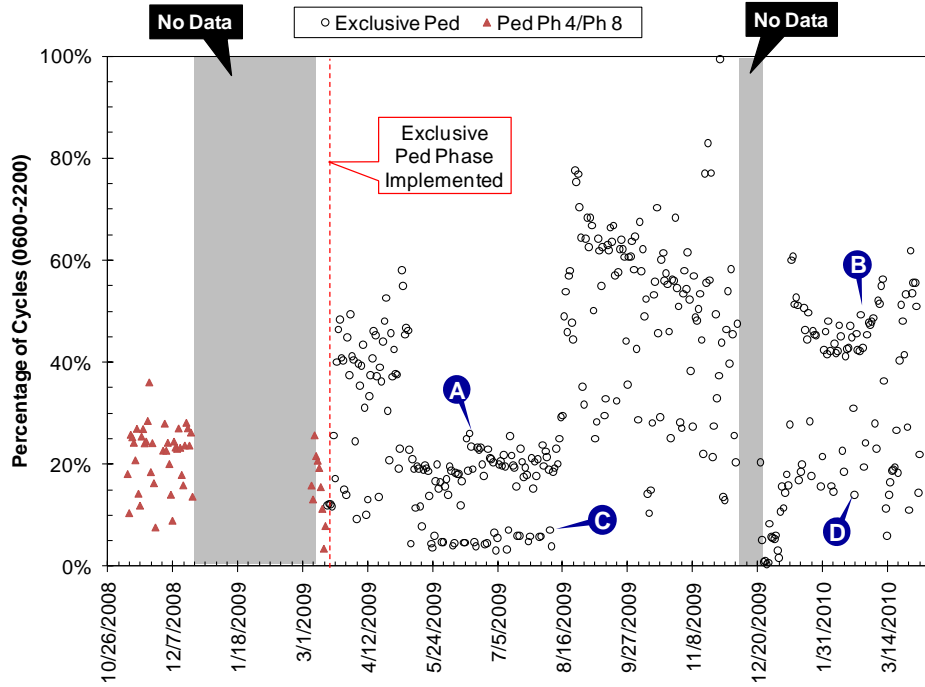
Category	Subcategory	Number of Samples	Percentage of Total
Pedestrian Phase Type	Traditional Phases	1,790	17%
	Exclusive Phases	8,688	83%
Weather (Precipitation)	No Precipitation	9,431	90%
	Rain (Non-frozen precip.)	753	7%
	Snow (Frozen precip.)	294	3%
Time of Day	0600-2200	6,984	67%
	Other	3,494	33%
Day of Week	Weekdays	7,406	71%
	Weekends	3,072	29%
Month of Year	January	832	8%
	February	672	6%
	March	1,334	13%
	April	816	8%
	May	744	7%
	June	720	7%
	July	744	7%
	August	744	7%
	September	720	7%
	October	744	7%
	November	1,256	12%
	December	1,152	11%
Academic Year	Academic Year	6,536	62%
	Summer Break	2,568	25%
	Other Breaks	1,374	13%
Special Events	Football game	160	2%
	Basketball game	156	2%
	Other	24	<1%
Total Number of 1-hour Samples		10,478	100%

3.5. Measurement Results

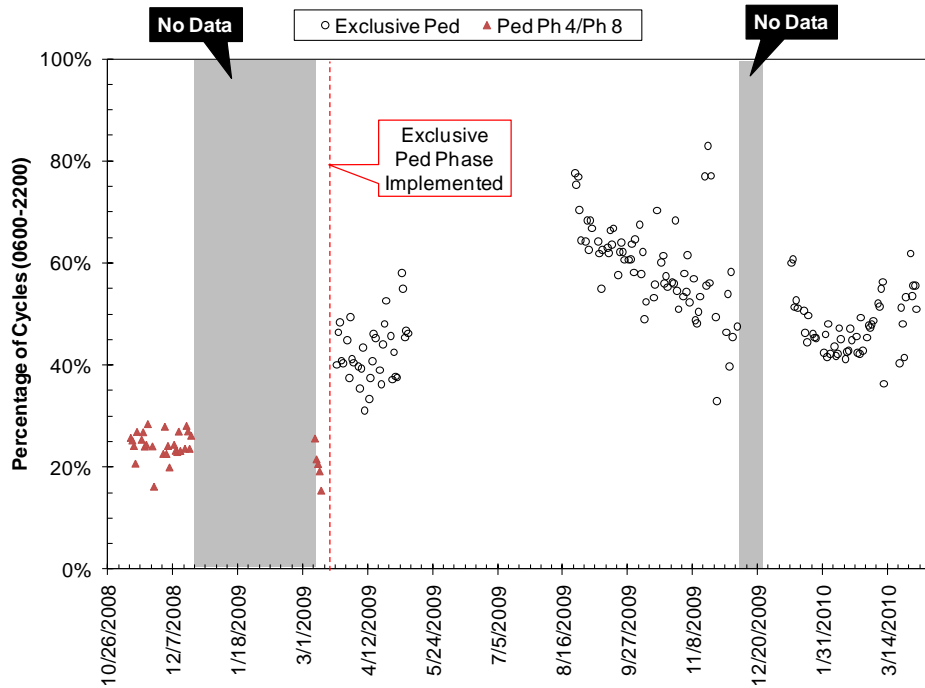
3.5.1. Daily, Weekly, and Annual Variation

Figure 3.3 shows the daily level of pedestrian utilization of phases crossing Northwestern. This plot shows the average percentage of cycles per hour (between 6:00 AM and 10:00 PM) for which the pedestrian movements Ped 4 and/or Ped 8 were served, either by traditional adjacent phases (Figure 3.2b, prior to March 17, 2009) or by exclusive pedestrian phases (Figure 3.2c, from March 17, 2009). Figure 3.3a shows all of the observed data, while Figure 3.3b shows only weekdays where class was in session. Two periods where data collection was temporarily unavailable are indicated by the gray regions in the plots. All data is shown after the implementation of the exclusive pedestrian phase.

The bimodal nature of the data with respect to two variables is clearly shown in Figure 3.3a. Pedestrian phase utilization is much lower during summer (callout A, approximately mid May through mid August) than during the academic year (callout B). Additionally, pedestrian phase utilization is consistently higher during weekdays (callouts A,B) than weekends (C,D), both during summer (A,C) and the academic year (B,D). In Figure 3.3b, where we eliminate all but days with classes in session, seasonal trends are also visible, as well as the impact of the introduction of the exclusive phase.



(a) All days when data was collected.



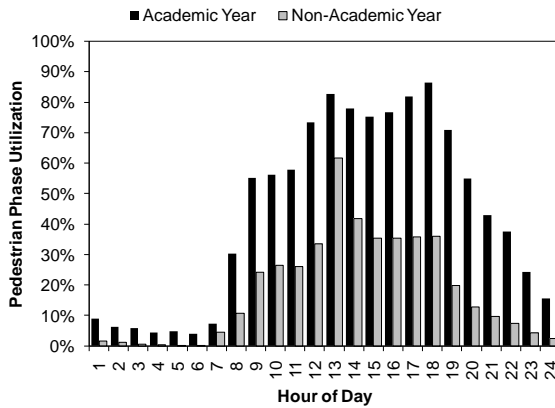
(b) Only days in the academic year with classes in session.

Figure 3.3 Percentage of cycles with pedestrian phases (during 0600-2200) crossing Northwestern Avenue (West Lafayette, IN).

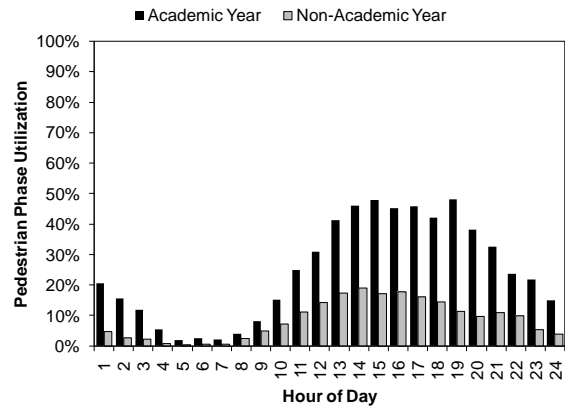
Figure 3.4 examines daily, weekly, and annual variations in greater detail.

- Pedestrian activity is very low in the early morning and late night. Overall trends are similar during both weekdays (Figure 3.4a) and weekends (Figure 3.4b). The two series of bars in these plots represent data from the academic year and non-academic year. On weekdays during the summer, ped phase usage is greatest at approximately noon (Figure 3.4a), while during the academic year the ped phase is sustained from noon through about 6:00 PM. Pedestrian activity is lower on weekends, but is still higher during the academic year than otherwise. Interestingly, there is a local spike in pedestrian activity at 1:00am on weekdays (Figure 3.4b) when classes are in session, the imprint of an activity pattern that clearly does not occur when the student population is absent.
- Figure 3.4c shows variations in pedestrian activity from 0600-2200, again with two series representing the academic year and non-academic year. The differences between weekdays and weekends, and between the academic year and non-academic year are about the same as that seen in the daily variation. Pedestrian activity is slightly less on Sunday than Saturday; there is very little difference from day to day among weekdays.
- Annual variations in pedestrian activity (during 0600-2200) are shown in Figure 3.4d. In this plot, the two series represent weekdays and weekends. Changes in pedestrian activity from month to month are largely dominated by student activity, with the least pedestrian activity during June and July and the greatest amount during September.

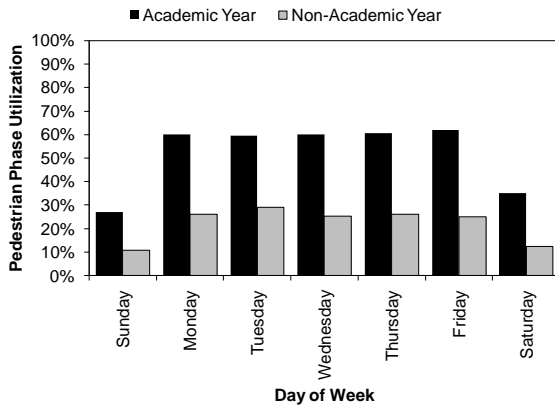
These results may be compared with yearlong study of pedestrian counts from an automatic pedestrian counter in a downtown area of Montpelier, Vermont (19). Daily variations are similar, with the exception of the late-night activity that occurs in our data during the academic year, most likely because of the activity patterns of university students. The annual variations are considerably different in our data because the activity patterns are so heavily dominated by student activity. This demonstrates the importance of local data collection for characterizing demand.



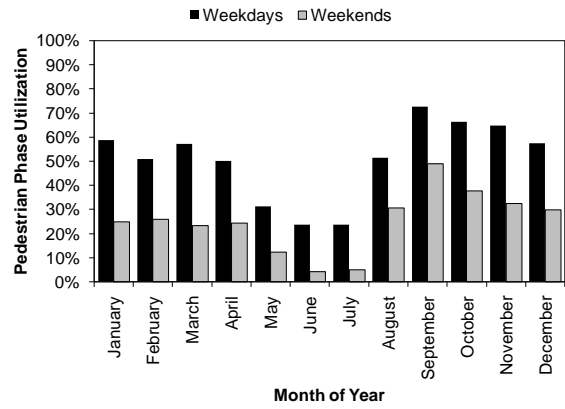
(a) Daily variation (weekdays).



(b) Daily variation (weekends).



(c) Weekly variation (0600-2200).

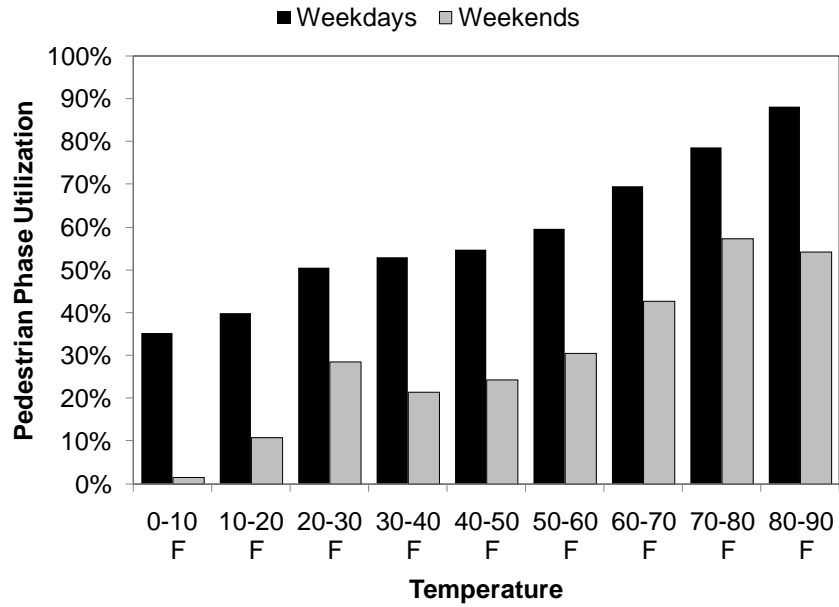


(d) Annual variation (0600-2200).

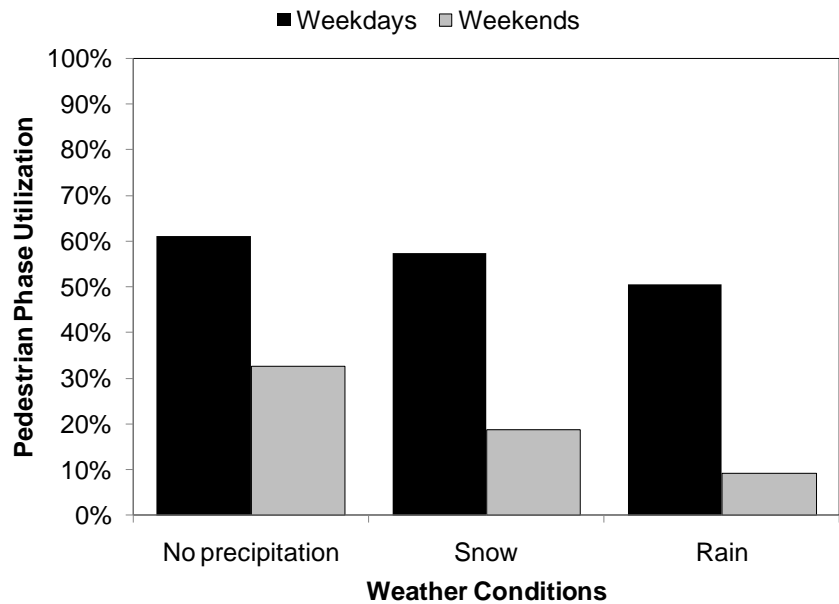
Figure 3.4 Daily, weekly, and annual variation in pedestrian phase utilization (all data from after implementation of exclusive pedestrian phase).

3.5.2. Impact of Weather

Weather conditions were matched for all of the 1-hour samples in the data set. Figure 3.5 illustrates the relationships between pedestrian phase utilization and temperature (Figure 3.5a) and precipitation (Figure 3.5b). Each plot shows two separate series for weekdays and weekends; data are shown for the academic year from 0600-2200, after the implementation of the exclusive pedestrian phase. Pedestrian activity tends to increase with temperature (Figure 3.5a); there is particularly little pedestrian activity on cold weekends. Pedestrian activity also tends to decrease during snow and rain (Figure 3.5b). The decreases are stronger on weekends than during weekdays, and the pedestrian phase is activated less often during rain than during snow.



(a) Temperature.



(b) Precipitation.

Figure 3.5 Variation in pedestrian phase utilization due to weather effects (all data from 0600-2200 during academic year after implementation of exclusive pedestrian phase).

3.5.3. Special Events

The proximity of the football stadium and basketball arena to the intersection of Stadium and Northwestern offers an excellent opportunity to observe the effects of special events on levels of pedestrian activity. A 1-hour sample was considered to be a “game event” within 8 hours of the beginning of a football game, and within 6 hours of the beginning of a game for a basketball event. For days within the academic year, pedestrian phase utilization averaged 62% during football game hours compared to 47% for non-football game hours (excluding the early morning hours). The corresponding numbers for basketball games are 51% and 48%. The impact of football games is evidently more substantial than that of basketball games, which is not unexpected given the relative attendance numbers discussed earlier.

3.5.4. Changes in Signal Operation

Figure 3.6 compares the percentage of cycles with pedestrian phases with conventional ped phases (Figure 3.6b) in use and with an exclusive ped phase (Figure 3.6c) in use. The data in this graph are from hours between 0600-2200 in November 2008 (conventional) and November 2009 (exclusive), and exclude special events, school breaks, and inclement weather. By November 2009, the exclusive phase had been in operation for eight months. The change in the percentage of cycles with pedestrian phases is shown at the top of the graph. For weekdays, average utilization increased from 45% to 63% while for weekends it increased from 17% to 30%. This data clearly shows that the addition of the exclusive pedestrian phase led to a moderate increase in the number of pedestrians using the intersection to cross Northwestern.

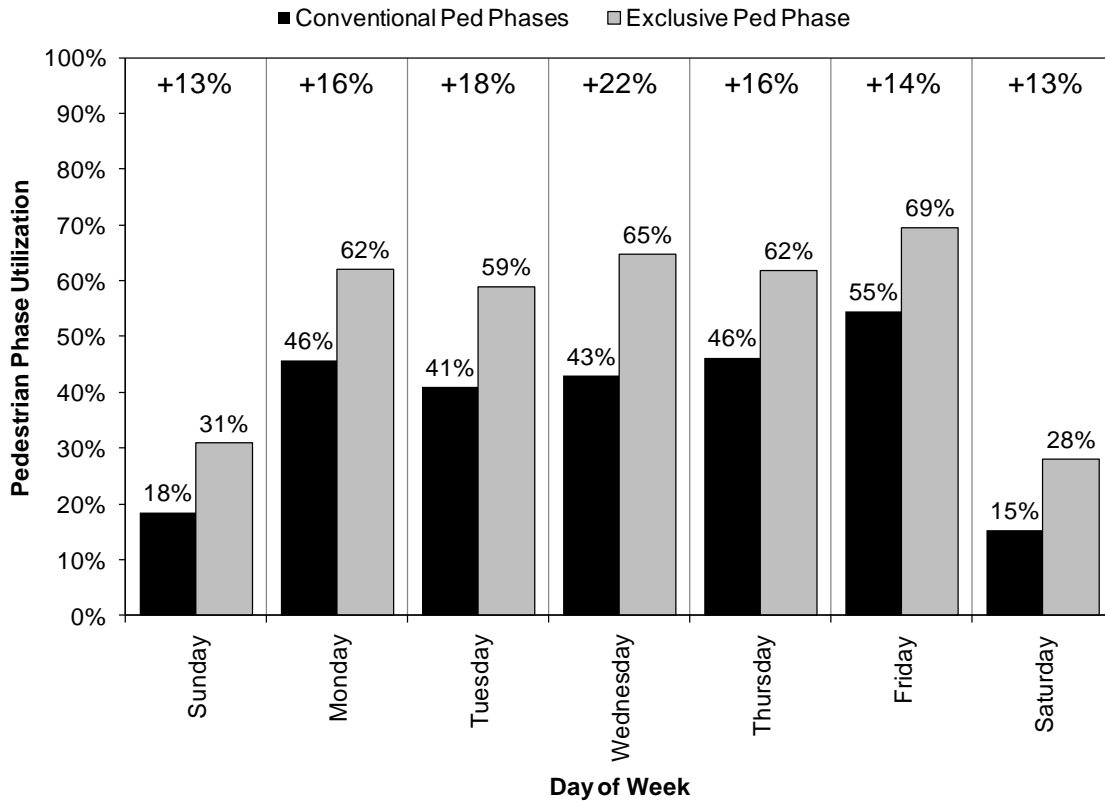


Figure 3.6 Percentage of cycles with pedestrian phases crossing Northwestern Avenue before and after exclusive pedestrian phase implementation (Data from November 2008 and November 2009, 0600-2200, excluding special events, breaks, and inclement weather).

3.6. Econometric Analysis

3.6.1. Model Development

To make a better sense of how several different variables concurrently influence pedestrian utilization, we estimate a statistical model and develop coefficients for the variables encoding the effects. The dependent variable, the percentage of cycles with pedestrian phases, is interval censored because it can only have values between 0% and 100%. There are consequentially many data points clustered at 0% and 100%. An ordinary least squares regression would not be appropriate for this dependent variable because it would be heavily skewed by the clustered data points at the ends of the possible range. An alternative model is a Tobit regression (8), which is intended for a continuous, censored dependent variable. Despite there being many modeled variables with censored data, Tobit regression has seen relatively little use in transportation, mainly in safety (26, 27, 28, 29) and economics (30, 31).

The data from the 10,478 1-hour observations were encoded into a series of dependent variables listed in Table 3.3. The majority of the variables were encoded as indicator variables (i.e., “1” means that the condition was true, while “0” means the condition was not true), with the exception of temperature, which was simply included as degrees Fahrenheit. Using temperature as a continuous variable resulted in better model fit than numerous indicator variables based upon temperature. Table 3.4 shows the model characteristics indicating the effects of the variables, their significance, and overall model characteristics. The goodness of fit is given by the Maddala pseudo- R^2 (32),

$$\text{Maddala pseudo-} R^2 = 1 - \exp \left[-LRT / N \right] \quad \text{Equation 3.1}$$

$$LRT = 2[LL(\hat{\beta}) - LL(0)] \quad \text{Equation 3.2}$$

where LRT is the likelihood ratio test statistic, $LL(\beta)$ is the log likelihood of the model at convergence, $LL(0)$ is the log-likelihood if the coefficients are constrained to zero, and N is the number of observations. The pseudo- R^2 value of 0.550 is not an unreasonable value for a large number of samples and data that is behavioral in nature.

Table 3.3 Descriptive statistics of variables used in the Tobit model.

Independent Variable	Min	Max	Mean	St. Dev.
Indicator of pedestrian phase configuration 1: exclusive ped phase; 0: conventional ped phases	0	1	0.842	0.365
Indicator of weekend 1: Saturday/Sunday; 0: other day of week	0	1	0.293	0.455
Indicator of break (weekday during academic calendar without classes in session) 1: break; 0: no break	0	1	0.131	0.338
Indicator of summer break 1: summer break; 0: not summer break	0	1	0.245	0.430
Indicator of August 1: August; 0: other month	0	1	0.071	0.257
Indicator of “daytime” hours (6:00 AM – 10:00 PM) 1: daytime hours; 0: other times	0	1	0.667	0.471
Indicator of “lunchtime” hours (11:00 AM – 1:00 PM) 1: lunchtime hours; 0: other times	0	1	0.083	0.277
Indicator of “PM peak” hours (3:00 PM – 6:00 PM) 1: PM Peak hours; 0: other times	0	1	0.125	0.331
Indicator of weekend nights (10:00 PM – 2:00 AM) 1: weekend nights; 0: other times	0	1	0.049	0.216
Temperature (Degrees Fahrenheit)	-0.9	93.0	49.637	19.221
Indicator of Rain (1: rain; 0: no rain)	0	1	0.072	0.258
Indicator of Snow (1: snow; 0: no snow)	0	1	0.028	0.165
Indicator of football game (1: game; 0: no game)	0	1	0.015	0.123
Indicator of basketball game (1: game; 0: no game)	0	1	0.015	0.121

3.6.2. Interpretation

The indicator variable shown in Table 3.4 for the exclusive pedestrian phase had a positive coefficient, which agrees with the increase in pedestrian activity related to the exclusive phase that was observed earlier in the raw data. The coefficient of the variable corresponding to the exclusive pedestrian phase, 0.0938, indicates that pedestrian phase usage increases by 9.38% after the addition of the feature. The magnitude of the coefficient is greater than variables based on weather effects. The number is slightly less than what is observed in the raw data (Figure 3.6) because of the influences of other variables in the model.

Three calendar-related variables were included to indicate weekends, breaks during the academic year, summer break, and the month of August. The weekend and break variables were highly significant with large negative coefficients, reflecting the strong decrease in pedestrian activity during weekends and breaks compared to other time periods, as discussed earlier and illustrated by Figure 3.4. The August variable captures the effects of students returning to campus, where pedestrian activity increases both during the portion of the month during summer break, and the portion after the start of classes.

Four time-of-day variables were defined indicating whether the percentage of cycles is obtained during the “daytime” (defined as 6:00 AM to 10:00 PM), “lunchtime” (11:00 AM to 1:00 PM), a “PM peak” time period (3:00 PM to 6:00 PM), or weekend nights (10:00 PM to 2:00 AM on weekends only). Each of these variables is highly significant, and has a fairly large positive coefficient, indicating the higher levels of pedestrian activity during these times of day. The daytime variable is the most significant variable among all the variables in this model, reflecting the fundamental difference in activity between day and night common to all times of the year (Figure 3.4a, Figure 3.4b). The lunchtime and PM peak variables capture local peaks during their respective time periods where pedestrian phase utilization is higher still. The weekend night indicator captures the local spike in pedestrian activity that takes place in the early morning hours, particularly during the academic year (Figure 3.4c).

Temperature was included as a continuous variable in the model. The coefficient of 0.00333 indicates an increase in the amount of pedestrian utilization by 0.3% of cycles per hour for each one-degree Fahrenheit increase in temperature. Pedestrian activity is greater during warmer weather. The model results are consistent with observations from the raw data (Figure 3.4a).

Table 3.4 Estimation of a Tobit model to describe pedestrian phase utilization.

Independent Variable	Coefficient	<i>t</i> -value	<i>P</i> -value
Constant term	-0.177	-18.094	< 0.001
Indicator of pedestrian phase configuration 1: exclusive ped phase; 0: conventional ped phases	0.0938	13.182	< 0.001
Indicator of weekend 1: Saturday/Sunday; 0: other day of week	-0.236	-41.252	< 0.001
Indicator of break (weekday during academic calendar without classes in session) 1: break; 0: no break	-0.269	-33.845	< 0.001
Indicator of summer break 1: summer break; 0: not summer break	-0.381	-53.024	< 0.001
Indicator of August 1: August; 0: other month	0.147	15.281	< 0.001
Indicator of “daytime” hours (6:00 AM – 10:00 PM) 1: daytime hours; 0: other times	0.431	69.470	< 0.001
Indicator of “lunchtime” hours (11:00 AM – 1:00 PM) 1: lunchtime hours; 0: other times	0.191	22.938	< 0.001
Indicator of “PM peak” hours (3:00 PM – 6:00 PM) 1: lunchtime hours; 0: other times	0.179	25.029	< 0.001
Indicator of weekend nights (10:00 PM – 2:00 AM) 1: lunchtime hours; 0: other times	0.305	23.667	< 0.001
Temperature (Degrees Fahrenheit)	0.00333	19.028	< 0.001
Indicator of Rain (1: rain; 0: no rain)	-0.0563	-6.240	< 0.001
Indicator of Snow (1: snow; 0: no snow)	0.0394	2.694	0.007
Indicator of football game (1: game; 0: no game)	0.272	14.659	< 0.001
Indicator of basketball game (1: game; 0: no game)	0.147	7.913	< 0.001
Number of observations		10,478	
Log likelihood at Convergence		1726.62	
Log likelihood at Zero		-2461.60	
Maddala Pseudo- R^2		0.550	

Two indicator variables for weather conditions were included: one for rain and one for snow. Both of these variables were significant, although less so than the others in the model. The coefficient for rain was negative, indicating that there is less utilization of pedestrian phases when rain occurred. This is in agreement with Figure 3.5b. The coefficient for snow, however, is positive, indicating that snow the effect of increasing pedestrian utilization. There are, therefore, some conditions under which utilization of pedestrian phases at the intersection increases because of snow. Perhaps this can be explained by the accumulation of snow along the shoulders and median strip on Northwestern Avenue, making it difficult for pedestrians to cross the street by stopping on the median, and encouraging them to use the marked crosswalk at the intersection.

Three indicator variables for special events were also included in the model. These reflected football games, basketball games, and when the first two weeks of classes took place. These three conditions reflected times of heightened pedestrian activity, as indicated by the large positive coefficients and high significance. The magnitude of these effects are about as strong as the day-to-day peaking at lunchtime and during the PM peak. Football games are a stronger generator of pedestrian activity than basketball games, agreeing with the prior discussion of the raw data and the relative attendance of the events.

3.6.3. Impact of Change in Pedestrian Service

The increase in pedestrian activity in response to the change in intersection operations can be viewed as an economic interaction of supply and demand (5), as illustrated by Figure 3.7. The improvement in pedestrian service is equivalent to the movement of the price-volume curve from “System A” to “System B” in the curve, with the area *DEBA* corresponding to the user benefit (reduction in user cost) and *AFGB* corresponding the amount of latent demand uncovered by the change in service. The exclusive pedestrian phase reduces user cost by providing a portion of the signal cycle with reduced pedestrian-vehicle conflicts as well as by allowing pedestrians to cross diagonally.

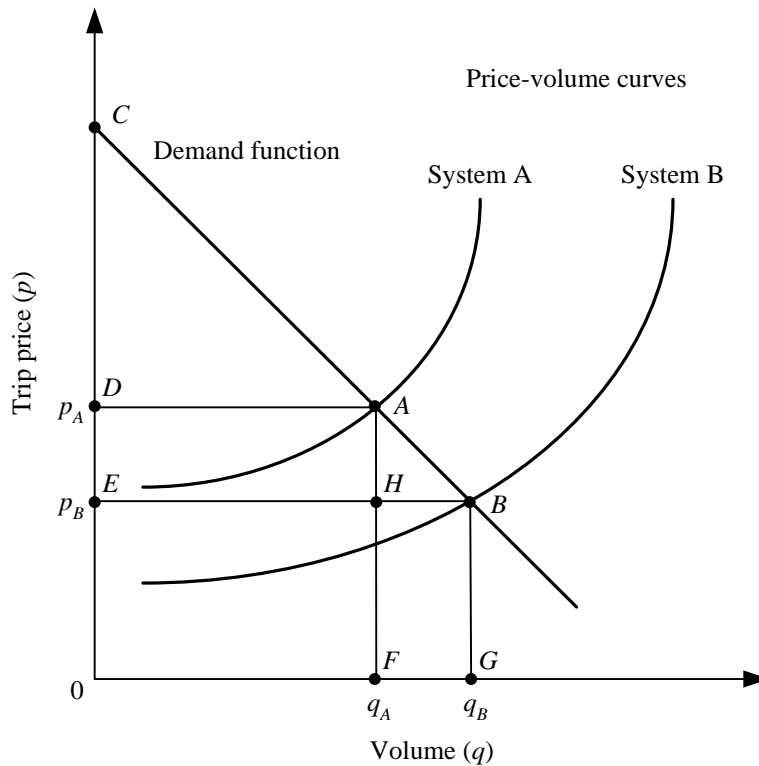


Figure 3.7 Economic concepts associated with changes in service in a transportation system, after Wohl and Hendrickson (5).

While it is clear that the exclusive pedestrian phase induced more pedestrian usage of the intersection, it seems unlikely that the demand for pedestrian trips across Northwestern Avenue increased as a result of the pedestrian phase. A more realistic explanation is that the increase in pedestrian utilization likely corresponds to a decrease in midblock pedestrian crossings elsewhere. While the exclusive pedestrian phase decreases user costs at the intersection, the characteristics of midblock crossings and their associated user costs have remained unchanged. As a consequence, more of the demand for crossing Northwestern was met by the intersection.

Similar effect can be observed in the impact of snow conditions. In the Tobit regression, the overall effect of the snow indicator variable was to increase pedestrian activity; this is illustrative of the interaction between intersection crossings and the midblock crossings. Snow makes midblock crossings more difficult by reducing the number of places on the median where crossing is feasible (*i.e.*, pedestrians are disinclined to stand at snow or ice

covered patches of the median in close proximity to two moving traffic streams). This may be interpreted as an increase in the cost of making a midblock crossing. As this cost increases, pedestrian activity at the intersection increases because it takes on more of the demand to cross the street. This observation agrees with findings by Muraleethan *et al.*, who reported changes in pedestrian routing due to winter weather (34).

3.7. Conclusion

This chapter proposed and demonstrated a methodology for quantifying the relative amount of pedestrian activity at a signalized intersection by tabulating the percentage of signal cycles per hour in which a pedestrian phase was actuated. While this performance measure does not directly use pedestrian counts, it can be used to characterize the relative change in demand, and offers the advantage of being implementable without installing additional infrastructure. The usefulness of the performance measure was demonstrated by documentation of changes in pedestrian utilization relative to daily, weekly, and annual variations; weather conditions (temperature and precipitation); special events; seasonal changes in activity patterns; and changes to pedestrian service at the intersection (implementation of an exclusive pedestrian phase). A Tobit model was estimated on this data to exemplify how these factors co-influenced the level of pedestrian utilization. The improvement of pedestrian service by implementation of the exclusive phase was associated with a 9.4% increase in utilization of the phase. This is interpreted economically as a decrease in user cost at the intersection relative to unchanging user cost for midblock crossings. This interpretation is consistent with the model findings with respect to snow conditions. Snow conditions lead to an increase in pedestrian activity at the intersection because of an increased cost of making midblock crossings due to the accumulation of snow in the path of those crossings.

CHAPTER 4. EVALUATION OF USER AND CARBON EMISSION COSTS

4.1. Introduction

This chapter performs a comparison of post-implementation outcomes for several optimization objectives including green arrival maximization and delay minimization. The measured changes in service resulting from these offsets are quantified and translated into user benefits. This study follows up from the 2009 offset optimization study discussed in Chapter 2. The arterial network was doubled in length and a variety of optimization objectives were investigated. This chapter focuses primarily on the measurement of user benefits. Additional details on the optimization methodology are described in (3).

4.2. Background on Offset Optimization Objectives

Signal offsets are typically designed by software packages that optimize offsets according to one of several mathematical objectives. One class of software packages attempts to *maximize the bandwidth* provided by signals through a corridor (35,36,37,38,39,40,41). Another major strategy is to model traffic patterns in the network and to *minimize disutility*, (e.g., delay) (42,43,44). The advantage of these models is that they not only optimize quantities such as delay and the number of stops but can be used to estimate user and environmental impacts. One disadvantage is that the delay calculation relies on numerous assumptions that might not accurately represent actual vehicle interaction with the signal.

A related objective that has been used in adaptive systems is to maximize the number of vehicles arriving on green (45,46,47). This is a simple calculation requiring fewer assumptions than delay models, making it ideal for real time calculation. The disadvantage of this approach is that the number of vehicles arriving on green cannot be used to directly characterize the external impacts of the signal system, and it has no intrinsic provision for clearing standing queues.

4.3. Offset Optimization Objectives

To illustrate the meaning of the different optimization objectives, we introduce the concept of the cyclic flow profile. A vehicle flow profile shows the probability of a vehicle arrival for a given time in cycle. Figure 4.1a shows an example flow profile, with a superimposed probability of green assuming fixed-time operations. In this example, each bin represents two seconds of the cycle. This profile is equivalent to that used by TRANSYT and ACS-Lite to display and evaluate signal performance. A profile is designated for each coordinated signal approach for a given analysis period, and represents arrival conditions for an “average cycle” in a given analysis period. Vehicle arrivals are collected by advance detectors and are projected to account for travel time to the stop bar.

Figure 4.1b shows the estimated number of queued vehicles based on the observed arrivals and the departures implied by the probability of green. Starting from the end of the green band, vehicles that arrive during red are assumed to join the queue, which grows until the beginning of green. After the beginning of green (and accounting for start-up lost time), vehicle departures reduce the queue size until the queue has dispersed. The number of queued vehicles during a given bin is equal to

$$q_i = \max(0, q_{i-1} + N_i - c_i) \quad \text{Equation 4.1}$$

where q_i is the queue length of the i^{th} bin, N_i is the number of vehicle arrivals associated with the bin, and c_i is the capacity or maximum number of departures in the bin, obtained from the probability of green G_i , number of cycles Q and saturation flow rate s from:

$$c_i = sQG_i \quad \text{Equation 4.2}$$

The total delay incurred by the vehicles is equal to the summation of the queue size, which gives the area between the arrival and departure profiles:

$$d = \sum_i q_i \quad \text{Equation 4.3}$$

The number of stops can be found making a few additional assumptions based on the queue profile and probability of green. We assume that vehicles that arrive during a

particular time in cycle will stop if a queue exists, or if the signal is red. Specifically, the number of stops per bin is calculated by:

$$S_i = \begin{cases} N_i, & \text{if } q_i > 0 \\ N_i(1 - G_i), & \text{if } q_i = 0 \end{cases} \quad \text{Equation 4.4}$$

Here, $(1 - G_i)$ represents the probability of the signal being red. A composite performance index combining both delay and stops can be specified as follows.

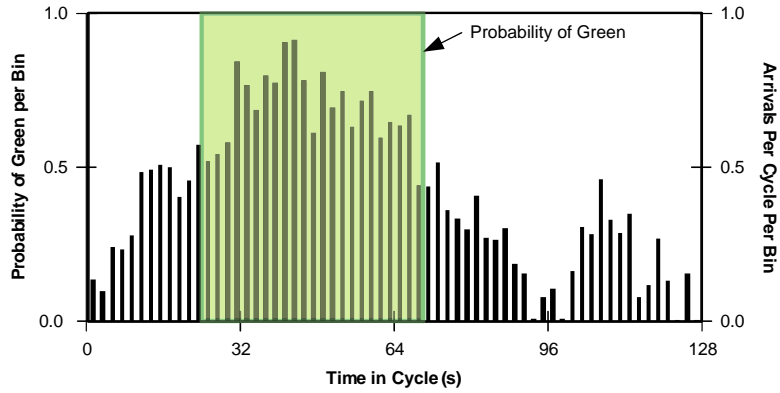
$$PI = d + k \sum_i S_i \quad \text{Equation 4.5}$$

Here, k is a weighting factor that converts stops into an equivalent number of seconds of delay. This is the PI used by early versions of TRANSYT. Subsequent versions have incorporated additional performance measures and convert the numbers into monetary cost equivalents. For this study, a value of $k = 20$ was used, which was found to make the value of the total stops approximately equal to delay.

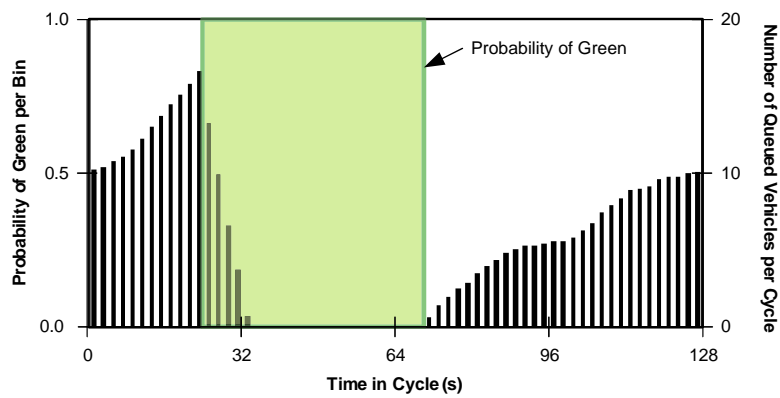
The flow profile in Figure 4.1a can also be used to calculate the number of arrivals on green (N_g):

$$N_g = \sum_i G_i N_i \quad \text{Equation 4.6}$$

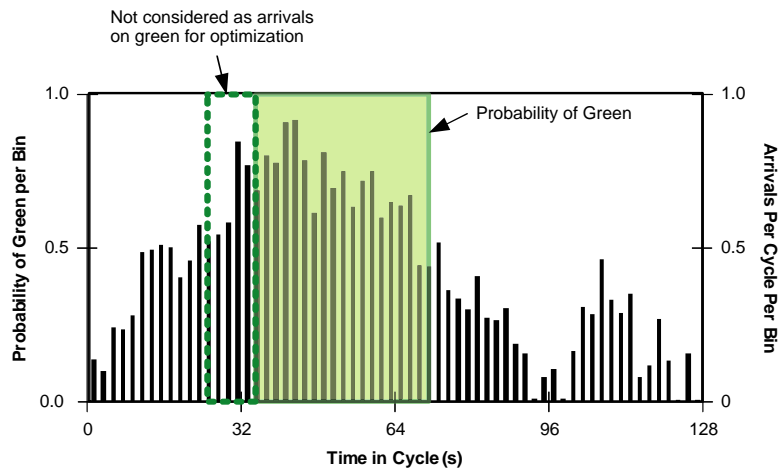
This is the portion of the vehicle profile captured by the green band. The calculation is equivalent to taking the vector dot product of G_i and N_i .



(a) Arrival flow profile and superimposed probability of green.



(b) Queue length profile.



(c) Alternative maximum arrivals on green objective.

Figure 4.1 Explanation of objective functions using flow profiles.

The number of arrivals on green is a simple calculation, but unlike delay or the number of stops, it does not take into consideration the presence of queues within the system. It seems likely that offsets designed to maximize N_g may give insufficient time for standing queues to disperse before coordinated platoons arrive. To account for this limitation, an alternative objective is proposed called the “alternative maximum on green,” in which a portion of time at the beginning of the green band is excluded from the green band for the purpose of optimization. This is illustrated by Figure 4.1c. Here, the first ten seconds (five bins) of the green band are considered to be “red” by the optimization process (i.e., they are excluded from Equation 4.6). Ideally, this would ensure a certain portion of green to clear queues before the heaviest portion of the platoon arrives at the signal.

This chapter examines the outcomes of four objectives defined in this section:

- Objective I. Minimize delay (Equation 4.3).
- Objective II. Minimize delay and stops (Equation 4.5).
- Objective III. Maximize arrivals on green. (Equation 4.6).
- Objective IV. Maximize arrivals on green with queue clearance time (Figure 4.1c).

Optimizing network offsets is a complex task because of interactions between offsets on a system. A variant of the Combination Method algorithm (43) was used to search for optimal offsets. This algorithm was selected because it systematically provided consistent, optimal offsets in less time than other algorithms. For more information on the offset adjustment algorithm, we refer the reader to extensive documentation available elsewhere (48, 49, 51).

4.4. Travel Time Measurement

The test arterial used in this study is SR 37 in Noblesville, Indiana (48,49,50). A map of the system is provided in Figure 4.2. This 5.2-mi (8.3 km) corridor consists of eight coordinated intersections that operate a common cycle length. At each intersection, a log-capable signal controller was deployed to collect signal event data (52). Additionally, probe vehicle travel time measurements were obtained from Bluetooth (BT) device MAC address matching (4, 53) using cases deployed at the entry points and one midpoint location in the system. From this arrangement, it was possible to obtain travel time measurements for the entire arterial (Case A to Case C), and for two smaller systems, System 1² (Case A to Case B) and System 2 (Case B to Case C).

For this report, we focus on outcomes for the Saturday time-of-day (TOD) plan, which runs from 0600-2200. Baseline data from Saturday, May 29, 2010 was used for the optimization procedure. The Saturday timing plan was selected because it was the focus of prior offset study in 2009 (4) for System 1, and because the offsets in System 2 were known to be sub optimal. Optimal offsets from the four objectives were subsequently deployed in June and July 2010. To optimize this 16-hour TOD plan, sixteen one-hour flow profiles per approach were constructed. The objective functions calculated independently for the sixteen one-hour flow profiles were then summed to obtain the value for the approach for the entire time of day. In a previous study, optimization outcomes from a smaller sub-portion of the day were found to be very similar to those for the entire sixteen-hour period (49). To analyze the travel time results, three-hour intervals beginning at 0600, 0900, 1200, 1500, and 1800 were used to group samples. Three hours was long enough to obtain reasonable numbers of samples but short enough to differentiate characteristics at different times of day.

² The four instrumented intersections in the network described in Chapter 2.

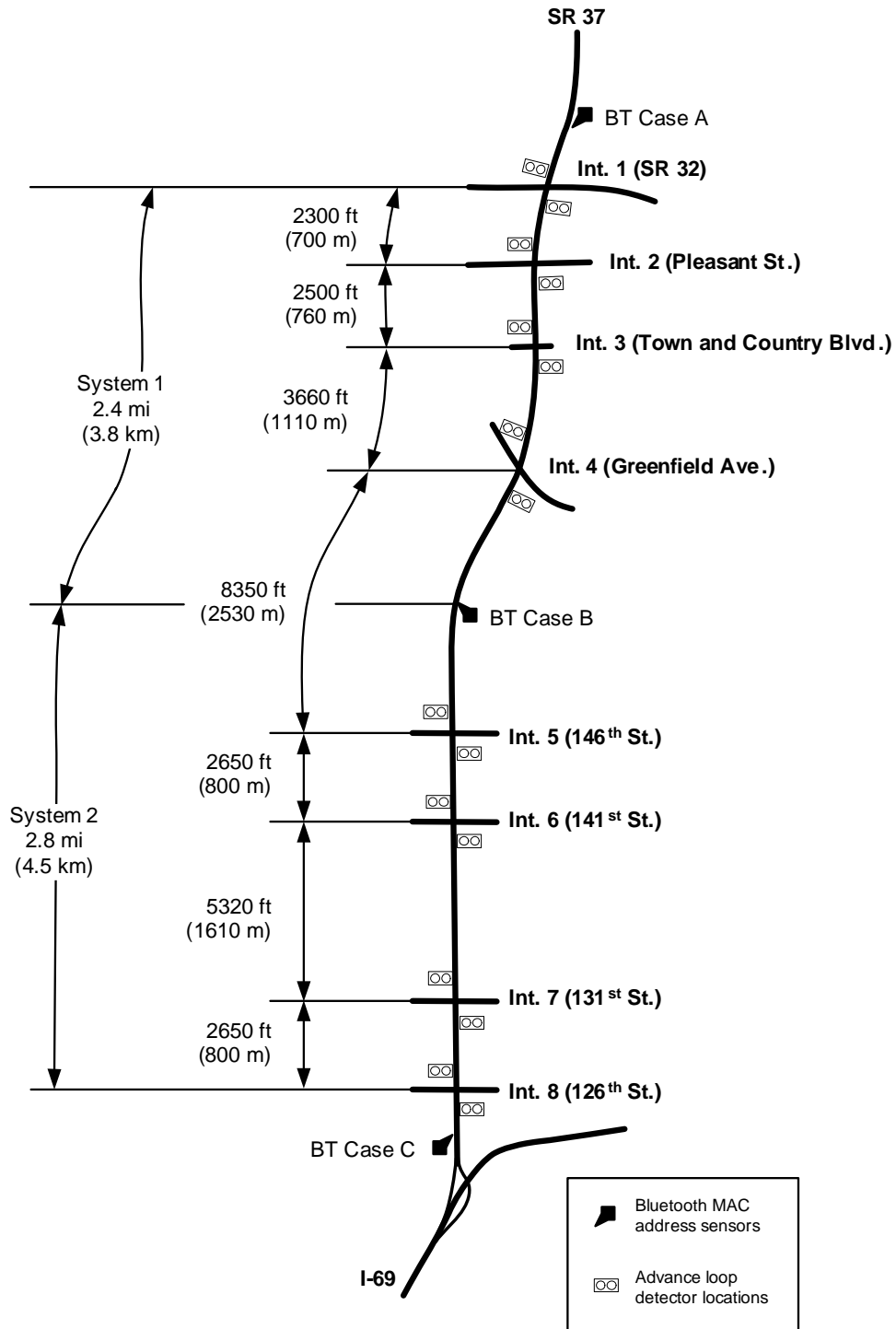
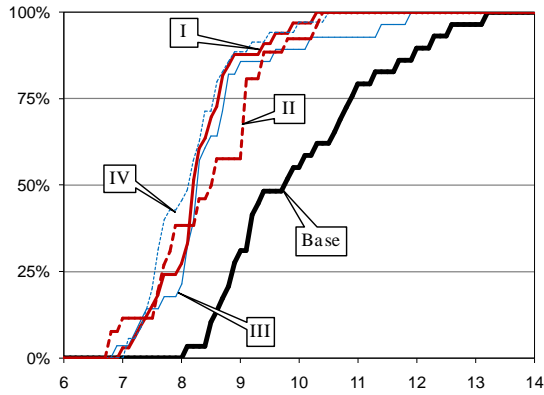


Figure 4.2 Map of the SR 37 Corridor (with equipment as of May 2010).

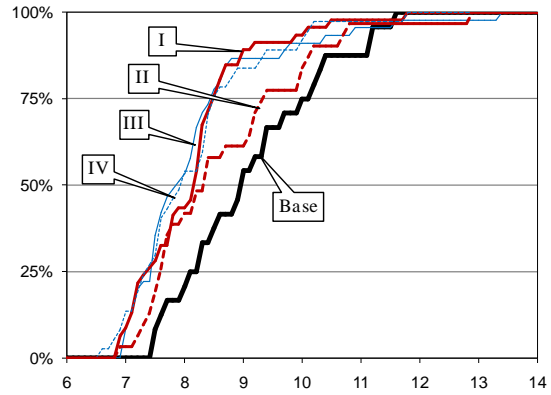
4.5. Outcomes from Implementation

Figure 4.3 shows cumulative frequency diagrams (CFDs) of the 1500-1800 interval for Saturdays during the baseline and with four different offset optimization objectives. The four lines in each plot are listed by objective number. The CFDs illustrate the movement of the central tendency of the travel time as the change in the median. If reliability is characterized as consistency in travel times, then greater consistency is associated with less variation in the measured travel times. In the CFD, this appears as a steeper line with a smaller interquartile range (IQR), the distance between the 25th percentile and the 75th percentile.

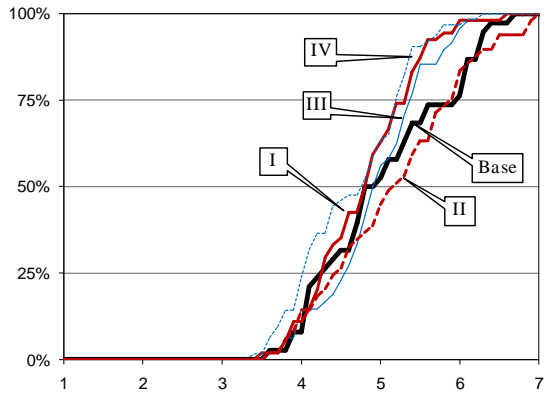
- CFDs of travel times along the entire arterial are shown for Southbound vehicles in Figure 4.3a and Northbound vehicles in Figure 4.3b. For this path, all four objectives clearly improved travel times compared to the baseline, with median travel times decreasing by approximately a minute. Obj. II did not perform as well as the others, but still yielded a net improvement, while the traces for the other three objectives are almost identical. For southbound traffic, the reliability seems to have improved (i.e., the slope of the optimized traces are steeper than the baseline).
- CFDs for travel times through System 1 are shown in Figure 4.3c and Figure 4.3d respectively for southbound and northbound vehicles. There is not much improvement in travel times compared to the baseline (in fact, Obj. II saw an increase in travel time for southbound vehicles). As mentioned before, offsets in this part of the arterial were already near optimal. However, the reliability for northbound vehicles has improved somewhat; the shape of the baseline curve in Figure 4.3d shows a plateau in the curve, a greater IQR. The other traces still exhibit a plateau, but it contains a much smaller portion of the observed vehicles.
- CFDs for travel times through System 2 are shown in Figure 4.3e and Figure 4.3 f respectively for southbound and northbound vehicles. This portion of the system had not been retimed in several years, and was known to have suboptimal offsets at two intersections. Consequently, a substantial improvement in travel times was achieved by all four objectives.



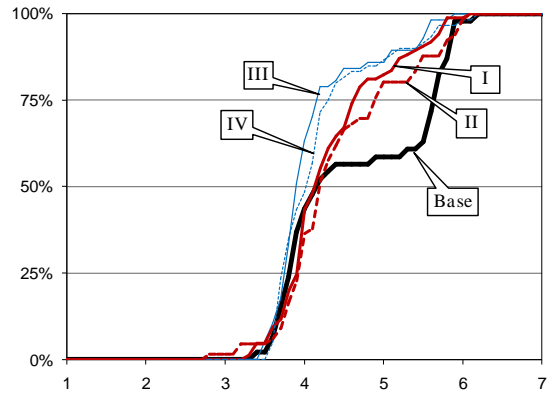
(a) Southbound, Case A to Case C.



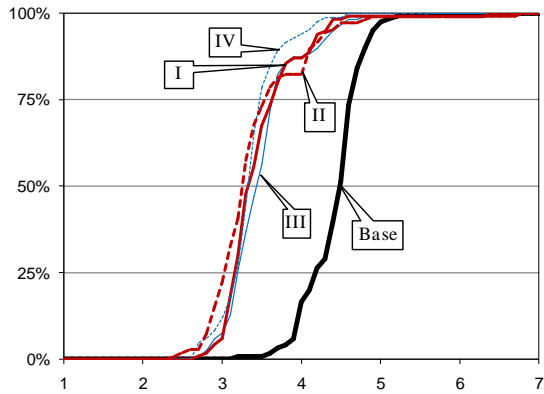
(b) Northbound, Case C to Case A.



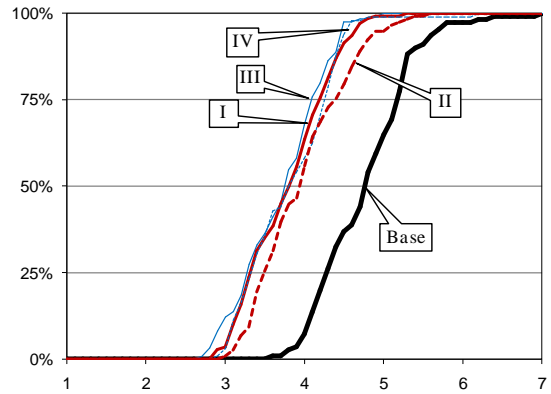
(c) Southbound, Case A to Case B.



(d) Northbound, Case B to Case A.



(e) Southbound, Case B to Case C.



(f) Northbound, Case C to Case B.

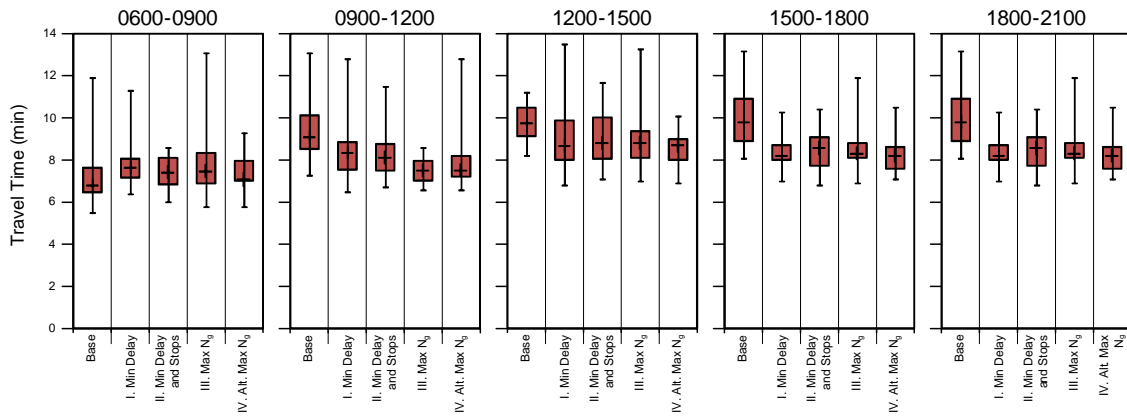
Figure 4.3 Cumulative frequency diagrams of probe vehicle travel times for alternative objective functions, Saturday, 1500-1800.

Note that the CFDs for System 2 (Figure 4.3e, Figure 4.3f) exhibit more consistent travel times than System 1 (Figure 4.3c, Figure 4.3d). That is, the slope of the CFDs are steeper for System 2 and the IQR is smaller than that of System 1. This can be attributed to the regular spacing of intersections in System 2, compared to irregular spacing for System 1, as shown in Figure 4.2 (the distance between Int. 6 and Int. 7 is approximately twice that of the neighboring links). Because of the irregular spacing, some tradeoffs are unavoidable between intersections on the links in System 1.

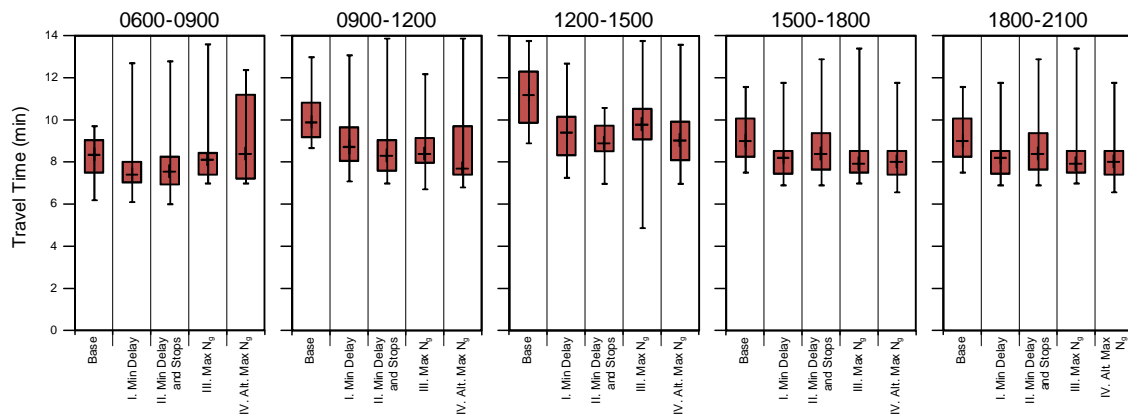
The Saturday signal timing plan covers a 16-hour TOD interval, during which traffic demand experiences some fluctuation. Figure 4.4 illustrates these fluctuations in box-whisker plots of travel times for the baseline offsets and the four optimized offsets. These are shown in five graphs representing five three-hour analysis subperiods. In each column, the line represents the range between the minimum and maximum values, with a marker showing the median value, while the box displays the 25th and 75th percentiles (and hence the IQR). Figure 4.4a shows travel times for northbound vehicles while Figure 4.4b shows travel times for southbound vehicles. Detailed information corresponding to these graphs are also presented in Table 4.1.

During most times of day, the median travel times were reduced by the optimized offsets, representing a net improvement in arterial travel time. This can be seen in both northbound and southbound direction for all time periods except the 0600-0900, when traffic volumes are relatively low and the mainline flows benefit from long green times due to lower demand for minor movements. For example, from 1500-1800, northbound travel times improved from 1.2–1.6 minutes and southbound travel times improved by 0.6–1.1 minutes, varying by objective. During several time periods, the IQR also decreased, indicating that the reliability of travel time improved. This is true of northbound vehicles during most time periods for nearly all objectives (Figure 4.4a), agreeing with earlier observations from the CFDs.

Comparing the performance across time periods characterizes the flexibility of the plan, or its ability to tolerate variations in traffic patterns throughout the day and provide similar performance for both northbound and southbound vehicles. Often, offsets are designed to treat a certain direction preferentially by time of day. In this study, no weighting was given to any particular movement, and volumes were relatively balanced throughout most of the day during the Saturday TOD plan interval. It is desirable to characterize whether this scheme caused either movement to suffer during particular times of day.



(a) Northbound.



(b) Southbound.

Figure 4.4 Travel time box-whisker plots for alternative optimization objectives by 3-hour time period, Saturdays, arterial (case A to case C).

Table 4.1 Arterial travel time (Case A to Case C) Statistics,
Saturdays, 3-hour analysis periods, with alternative offsets in use.

Time	MOE	Southbound					Northbound				
		Baseline	Obj. I	Obj. II	Obj. III	Obj. IV	Baseline	Obj. I	Obj. II	Obj. III	Obj. IV
Saturday 0600-0900	25 %	7.5	7.0	6.9	7.4	7.2	6.5	7.2	6.9	6.9	7.0
	Median	8.4	7.4	7.6	8.1	8.4	6.8	7.7	7.4	7.5	7.1
	75 %	9.1	8.0	8.2	8.5	11.2	7.7	8.1	8.1	8.3	8.0
	IQR	1.6	1.0	1.3	1.1	4.0	1.2	0.9	1.3	1.5	1.0
	Mean	8.2	7.8	7.9	8.2	9.1	7.3	7.7	7.4	8.1	7.4
	St. Dev.	1.3	1.6	1.7	1.4	2.1	1.6	1.0	0.9	2.0	1.0
	N	10	22	22	19	9	19	26	11	16	10
	t-value		-0.64	-0.51	0.05	1.24		1.01	0.20	1.29	0.05
	P-value		0.527	0.614	0.957	0.232		0.318	0.842	0.208	0.960
Saturday 0900-1200	25 %	9.2	8.1	7.6	8.0	7.4	8.5	7.6	7.5	7.0	7.2
	Median	9.9	8.7	8.3	8.4	7.7	9.1	8.4	8.1	7.5	7.5
	75 %	10.8	9.6	9.1	9.2	9.7	10.1	8.9	8.8	8.0	8.2
	IQR	1.6	1.6	1.5	1.2	2.3	1.6	1.3	1.3	0.9	1.0
	Mean	10.2	8.9	8.6	8.6	8.6	9.5	8.4	8.3	7.5	7.8
	St. Dev.	1.2	1.2	1.5	1.1	1.9	1.7	1.3	1.1	0.5	1.1
	N	29	40	39	32	33	25	36	39	22	30
	t-value		-4.67	-4.77	-5.42	-3.87		-2.93	-3.67	-5.56	-4.65
	P-value		<0.001	<0.001	<0.001	<0.001		0.005	0.001	<0.001	<0.001
Saturday 1200-1500	25 %	9.9	8.3	8.5	9.1	8.1	9.1	8.0	8.1	8.1	8.0
	Median	11.2	9.4	8.9	9.8	9.1	9.8	8.7	8.8	8.8	8.7
	75 %	12.3	10.2	9.8	10.6	10.0	10.5	9.9	10.0	9.4	9.0
	IQR	2.4	1.9	1.2	1.5	1.9	1.4	1.9	2.0	1.3	1.0
	Mean	11.2	9.4	9.0	9.9	9.3	9.8	9.0	9.0	8.9	8.5
	St. Dev.	1.6	1.3	1.0	1.5	1.7	0.8	1.4	1.2	1.2	1.0
	N	25	34	34	31	44	30	34	28	42	25
	t-value		-4.86	-6.62	-3.25	-4.47		-2.54	-2.94	-3.41	-5.19
	P-value		<0.001	<0.001	0.002	<0.001		0.014	0.005	0.001	<0.001
Saturday 1500-1800	25 %	8.3	7.4	7.7	7.5	7.4	8.9	8.0	7.7	8.1	7.6
	Median	9.0	8.2	8.4	7.9	8.0	9.8	8.2	8.6	8.3	8.2
	75 %	10.1	8.5	9.4	8.5	8.5	10.9	8.7	9.1	8.8	8.6
	IQR	1.8	1.1	1.7	1.0	1.1	2.0	0.7	1.4	0.7	1.0
	Mean	9.2	8.2	8.7	8.2	8.2	10.1	8.3	8.5	8.6	8.2
	St. Dev.	1.2	1.0	1.3	1.3	1.1	1.4	0.7	1.0	1.1	0.8
	N	24	46	31	45	37	29	33	26	28	35
	t-value		-3.62	-1.33	-2.92	-3.25		-6.23	-4.73	-4.50	-6.78
	P-value		0.001	0.188	0.005	0.002		<0.001	<0.001	<0.001	<0.001
Saturday 1800-2100	25 %	8.7	7.3	7.4	7.6	7.4	8.1	7.2	6.8	7.0	7.0
	Median	9.1	7.6	7.9	8.0	7.9	8.6	7.8	7.5	7.5	7.6
	75 %	9.5	8.3	8.3	8.3	8.1	9.2	8.3	8.1	8.1	7.9
	IQR	0.9	1.1	0.9	0.8	0.7	1.1	1.1	1.3	1.1	0.9
	Mean	9.1	7.7	8.2	8.1	8.4	9.1	8.0	7.7	7.6	7.6
	St. Dev.	0.6	0.6	1.5	1.2	2.1	1.5	1.3	1.0	0.7	1.3
	N	40	27	33	24	28	18	27	24	38	28
	t-value		-9.06	-3.35	-4.31	-1.87		-2.49	-3.58	-5.11	-3.50
	P-value		<0.001	0.001	<0.001	0.066		0.017	0.001	<0.001	0.001

Both Figure 4.4a and Figure 4.4b illustrate increasing an increase in median travel times around 1200-1300 compared to the other time periods. Northbound and southbound travel times are more similar after optimization than the baseline case. For example, from Table 4.1, during the 1200-1500 time period, under the baseline offsets the median northbound travel time was 1.4 min greater than the southbound travel time (11.2 versus 9.8 min). With optimal offsets, the difference between median northbound and southbound travel times decreased, with the magnitude of the decrease varying by objective. For example, under Obj. II, northbound travel times were only 0.1 min longer than southbound travel times, while Obj. III was less flexible, with a 1.0-min difference between the two. Similar changes can be observed in the other time periods.

Table 4.1 provides several statistical measures in addition to the median travel time and the IQR. An alternative measure of central tendency are the mean and standard deviations. We have highlighted the median and IQR because they are directly related to the CFDs and box-whisker plots and are less sensitive to outliers. However, similar trends are observable in the mean and standard deviation. Table 4.1 also displays the results of a *t*-test between the baseline offsets and the four optimized offsets. With the exceptions of the 0600-0900 time period, and for Objective II during 1500-1800, the *t*-test revealed statistically significant changes in travel time, with P-values showing confidence above the 95% level in all cases, and above 99% for most. This reconfirms earlier results (4) demonstrating the ability of MAC address matching to obtain sufficient data sets to show statistical significance in changes in travel time.

4.6. User Benefit Estimation

The following equations were applied to establish a method for comparing the optimized arterial travel time (TT) to a base travel time:

$$\Delta TT = TT_{Base(section)} - TT_{Objective(section)} \quad \text{Equation 4.7}$$

where $TT_{Base(section)}$ was the arterial travel time measured in minutes for a specified section (Figure 4.2, System 1 or System 2) and direction (northbound, southbound) running baseline offsets and $TT_{Objective(section)}$ was the travel time for each section, after optimal offsets were implemented based upon the four objectives. The change in travel time was associated with a user cost savings using the formulas outlined here. This cost estimation methodology is based on the 2009 Transportation Urban Mobility Report (4). Costs for *trucks* are given by

$$USER_t = \Delta TT * Vol * \%T * PPV_t * \frac{\$102.12}{hr} * \frac{1 hr}{60 min} \quad \text{Equation 4.8}$$

where $USER_t$ is the user cost for a commercial vehicle, Vol is the volume (number of vehicles) measured for the study period, $\%T$ is the assumed percentage of commercial trucks (2% for Saturday), and PPV_t is the number of passengers per vehicle (1 for commercial trucks). The \$102.12 amount represents the time value of money for commercial vehicles and is taken from the 2009 Transportation Urban Mobility Report (4). This value does not reflect excess fuel consumption. When ΔTT is positive, the outcomes of the equation reflect a user savings. Costs for passenger cars are given by

$$USER_c = \Delta TT * Vol * \%C * PPV_c * \frac{\$15.47}{hr} * \frac{1 hr}{60 min} \quad \text{Equation 4.9}$$

where $USER_c$ is the user cost for a passenger vehicle, $\%C$ is the assumed percentage of passenger vehicles (98% for Saturday), PPV_c is assumed to be 1.2, and a lower time value of money at \$15.47 per hour (4) is applied.

In addition to user costs, potential savings in fuel consumption and associated changes in CO₂ emissions can be derived from the following equations.

$$FUEL = \Delta TT * Vol * \frac{0.87 \text{ gal}}{\text{hr}} * \frac{1 \text{ hr}}{60 \text{ min}} \quad \text{Equation 4.10}$$

In Equation 4.10, *FUEL* is the change in the amount of fuel consumed (gallons), which is a savings when ΔTT is positive. Using conversion factors from Argonne National Laboratory, a passenger car that idles at 1,000 rpm with air conditioning on 50% of the time can be expected to consume 0.87 gallons of gasoline per hour, or 0.0145 gallons per minute (55, 56). This number was used to conservatively estimate the change in fuel consumption for all vehicle types associated with changes in travel time. For decreases in travel time (positive ΔTT), the amount of CO₂ emissions that are prevented are calculated from the following two equations:

$$CO_2 = FUEL * \frac{19.4 \text{ lbs}}{\text{gal}} * \frac{1 \text{ ton}}{2000 \text{ lbs}} \quad \text{Equation 4.11}$$

$$CC = CO_2 * \frac{\$22}{\text{ton}} \quad \text{Equation 4.12}$$

Here, *CC* represents the “CO₂ cost.” According to the EPA, the amount of CO₂ emitted when a gallon of gasoline burns is approximately 19.4 lbs/gallon (57). The monetary equivalent of the CO₂ is assumed to be approximately \$22/ton of CO₂ produced (58).

The results shown in Table 4.2 illustrate the benefit for system users based on above analysis. The savings is calculated from measured reductions in travel time from probe vehicle data and volumes measured from count detectors and logged in the signal event data. By optimizing Saturday offsets, user cost reductions ranging from \$471,817 (Objective III) to \$600,073 (Objective IV) could be realized, depending on which offsets are permanently implemented. The associated reduction in CO₂ emissions was found to range from 197 to 250 tons of CO₂ per year.

Table 4.2 Summary of cost savings for alternative optimization objectives.

Objective		Daily				Multiplier	Annual		
		Total Time Saved (veh-min)	CO ₂ Emission Reduction (tons)	CO ₂ Savings	User Benefits		CO ₂ Emission Reduction (tons)	CO ₂ Savings	User Benefits
(a) System 1, Northern Section									
I	Min Delay	5032	0.71	\$16	\$1,697	52	37	\$810	\$88,233
II	Min Delay and Stops	3813	0.54	\$12	\$1,286	52	28	\$614	\$66,864
III	Max N_g	1760	0.25	\$5	\$593	52	13	\$283	\$30,855
IV	Alt. Max N_g	7883	1.11	\$24	\$2,658	52	58	\$1,268	\$138,229
(b) System 2, Southern Section									
I	Min Delay	24386	3.43	\$75	\$8,223	52	178	\$3,924	\$427,614
II	Min Delay and Stops	25327	3.56	\$78	\$8,541	52	185	\$4,075	\$444,111
III	Max N_g	25147	3.54	\$78	\$8,480	52	184	\$4,046	\$440,962
IV	Alt. Max N_g	26338	3.70	\$81	\$8,882	52	193	\$4,238	\$461,845
(c) System 1 and System 2, Arterial									
I	Min Delay	29418	4.14	\$91	\$9,920	52	215	\$4,733	\$515,847
II	Min Delay and Stops	29140	4.10	\$90	\$9,826	52	213	\$4,689	\$510,976
III	Max N_g	26907	3.78	\$83	\$9,073	52	197	\$4,329	\$471,817
IV	Alt. Max N_g	34221	4.81	\$106	\$11,540	52	250	\$5,506	\$600,073

4.7. Conclusion

This chapter developed and independently validated the benefits of offset optimization for several objectives using directly measured probe vehicle travel time to quantify delay, user cost savings, and environmental impact. The results for all four objectives were similar in terms of the reduction in travel time savings (Table 4.1) and the overall environmental impact and the user benefit associated with reductions in travel time (Table 4.2). The outcomes of the delay-based optimization objectives were generally close to the outcomes of green arrival maximization, as shown in Table 4.2 and in several performance measure graphics (Figure 4.3, Figure 4.4). These results demonstrate that green arrival maximization can be used to effectively optimize offsets with the same level of benefit as derived from delay minimization. In addition, we proposed using the interquartile range (IQR) as a basis for characterizing travel time reliability, and demonstrated its use in comparing the baseline and post-implementation travel times for the four optimization objectives.

In closing, measured travel time results are a compelling tool to communicate the value of investments in traffic signal systems to the public and to elected decision makers. This information is essential to obtain and communicate, particularly for system improvements such as signal retiming that are relatively low visibility but can have a substantial environmental and economic impact.

CHAPTER 5. CONCLUSION

This report demonstrated the use of high-resolution signal event data and Bluetooth device MAC address matching to quantify changes in traffic signal system performance. Chapters 2 and 3 presented methods for assessing whether changes in demand were induced by signal retiming. Chapter 4 presented a method for quantifying user cost and environmental impact associated with a change in travel time, and also discussed ways to interpret the distribution of travel times to characterize travel time reliability.

In Chapter 2, we tracked changes in traffic volumes over 21 months to determine whether any demand was induced by a 1.9-minute improvement in northbound travel times for a Saturday signal timing plan. Traffic counts were adjusted for seasonal variation and revealed a 2.6% increase in volume. A *t*-test of the before and after data showed low statistical significance, which is interpreted as meaning that the demand is rather inelastic to cost, at least for Saturdays within the observed range of improvement.

Chapter 3 focuses on the implementation of an exclusive pedestrian phase at a fully-actuated urban intersection. A surrogate measure of pedestrian demand is proposed, the percentage of signal cycles with actuated pedestrian phases. This variable is tracked over an 18 month time period. The impacts of season, time of day, special events, weather, and changes in signal timing are interpreted as a series of variables that collectively influence the pedestrian demand. A Tobit model is used to interpret these variables. The exclusive pedestrian phase is observed to induce a 9% increase in pedestrian phase utilization.

Chapter 4 demonstrates the use of travel time data in describing travel time reliability and quantifying user costs and economic impact of signal retiming. Using data from a study comparing four alternative offset optimization objectives, the decrease in travel time from offset optimization is found to induce user cost savings on the order of half a million dollars (varying by objective) and a reduction of hundreds of tons of CO₂. Distributions of travel time as described by cumulative frequency diagrams are used to describe the change in travel time reliability.

REFERENCES

1. Day, C.M., H. Premachandra, and D.M. Bullock. "Observation of Traffic Patterns and Changes in Demand Due to Signal Timing Plan Changes." White Paper SPR-3208-1, Joint Transportation Research Program, Purdue University, West Lafayette, IN, May 2010.
2. Day, C.M., H. Premachandra, and D.M. Bullock. "Characterizing the Impacts of Phasing, Environment, and Temporal Factors on Pedestrian Demand at Traffic Signals." Paper No. 11-0220, submitted to Transportation Research Record, July 2010.
3. Day, C.M., T.M. Brennan, A.M. Hainen, S.M. Remias, H. Premachandra, J.R. Sturdevant, G. Richards, J.S. Wasson, and D.M. Bullock. "Reliability, Flexibility, and Environmental Impact of Alternative Arterial Offset Optimization Objective Functions." Paper No. 11-0036, submitted to Transportation Research Record, July 2010.
4. Day, C.M., R. Haseman, H. Premachandra, T.M. Brennan, J. Wasson, J.R. Sturdevant, and D.M. Bullock. "Visualization and Assessment of Arterial Progression Quality Using High Resolution Signal Event Data and Measured Travel Time." *Transportation Research Record*, Transportation Research Board of the National Academies, Washington, DC, in press, to appear 2010.
5. Wohl, M. and C. Hendrickson. *Transportation Investment and Pricing Principles*. John Wiley and Sons, 1985.
6. Hauer, E. "The harm done by tests of significance." *Accident Analysis and Prevention*, Vol. 36, pp. 495-500, 2004.
7. Hubbard, S.M.L., D.M. Bullock, and C.M. Day. "Integration of real-time pedestrian performance measures into existing infrastructure of traffic signal system." *Transportation Research Record No. 2080*, Transportation Research Board of the National Academies, Washington, DC, pp. 37-47, 2008.
8. Tobin, J. "Estimation of relationships for limited dependent variables." *Econometrica*, Vol. 26, pp. 24-36, 1958.
9. Porter, C., J. Suhrbier, and W.L. Schwartz. "Forecasting Bicycle and Pedestrian Travel: State of the Practice and Research Needs." In *Transportation Research Record No. 1674*, Transportation Research Board of the National Academies, Washington, D.C., 1999, pp. 94-101.
10. Ewing, R. and R. Cervero. "Travel and the Built Environment: A Synthesis." In *Transportation Research Record No. 1780*, pp. 87-113, Transportation Research Board of the National Academies, Washington, D.C., 2001.
11. Moudon, A.V., P.M. Hess, J.M. Matlick, and N. Pergakes. "Pedestrian Location Identification Tools: Identifying Suburban Areas with Potentially High Latent Demand for Pedestrian Travel." In *Transportation Research Record No. 1818*, pp. 94-101, Transportation Research Board of the National Academies, Washington, D.C., 2002.
12. Pulugurtha, S.S. and S.R. Repaka. "Assessment of Models to Measure Pedestrian Activity at Signalized Intersections." In *Transportation Research Record No. 2073*, pp. 39-48, Transportation Research Board of the National Academies, Washington, D.C., 2008.
13. Schneider, R., R. Patton, J. Toole, and C. Raborn. *Pedestrian and Bicycle Data Collection in United States Communities: Quantifying Use, Surveying Users, and Documenting Facility Extent*. Pedestrian and Bicycle Information Center, Highway Safety Research Center, University of North Carolina, Chapel Hill, January 2005.

14. Green-Roesel, R., M.C. Diogenes, D.R. Ragland, and L.A. Lindau. *Effectiveness of a Commercially Available Automated Pedestrian Counting Device in Urban Environments: Comparison with Manual Counts*. Traffic Safety Center, University of California, Berkeley, 2007.
15. Bell, A. Technology Innovations: Infrared Bicyclist and Pedestrian Counter. In *Bike/Ped Professional: Journal of the Association of Pedestrian and Bicycle Professionals*, pp. 4-5, 2006.
16. Schneider, R.J., L.S. Arnold, and D.R. Ragland. *A Methodology for Counting Pedestrians at Intersections: Using Automated Counters to Extrapolate Weekly Volumes from Short Manual Counts*. Traffic Safety Center, University of California, Berkeley, 2008.
17. Ling, B., S. Tiwari, Z. Li, and D.R.P. Gibson. "A Multi-Pedestrian Detection and Counting System Using Fusion of Stereo Camera and Laser Scanner." Proc., SPIE Optics and Photonics, California, August 2010.
18. Schneider, R.J., L.S. Arnold, and D.R. Ragland. "Pilot Model for Estimating Pedestrian Intersection Crossing Volumes." In *Transportation Research Record No. 2140*, Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 13-26.
19. Aultman-Hall, L., D. Lane, and R.R. Lambert. "Assessing Impact of Weather and Season on Pedestrian Traffic Volumes." In *Transportation Research Record No. 2140*, pp. 35-43, Transportation Research Board of the National Academies, Washington, D.C., 2009.
20. Hubbard, S.M.L., D.M. Bullock, and C.M. Day. "Integration of real-time pedestrian performance measures into existing infrastructure of traffic signal system." *Transportation Research Record No. 2080*, Transportation Research Board of the National Academies, Washington, DC, pp. 37-47, 2008.
21. Hubbard, S.M.L., D. M. Bullock, and F.L. Mannering, "Right-Turns on Green and Pedestrian Level of Service: A Statistical Assessment," *ASCE Journal of Transportation Engineering*, Vol. 135, No. 4, pp. 153-159, April 2009.
22. City Bus of Greater Lafayette, Indiana ridership reports. <http://www.gocitybus.com/ridership.html>. Accessed on July 15, 2010.
23. National Weather Service climate data. <http://www.weather.gov/climate>. Accessed on July 15, 2010.
24. Smaglik, E.J., Sharma, A., Bullock, D.M., Sturdevant, J.R., and Duncan, G. "Event-Based Data Collection for Generating Actuated Controller Performance Measures." *Transportation Research Record No. 2035*, Transportation Research Board of the National Academies, Washington, DC, pp. 97-106, 2007.
25. Tobin, J. "Estimation of relationships for limited dependent variables." *Econometrica*, Vol. 26, pp. 24-36, 1958.
26. Weiss, A.A. "The effects of helmet use on the severity of head injuries in motorcycle accidents." *J. Am. Stat. Assoc.*, Vol. 87, pp. 48-56, 1992.
27. Talley, W.K. "Safety Investments and Operating Conditions: Determinants of Accident Passenger-Vessel Damage Cost." *Soc. Methods. Res.* Vol. 31, pp. 364-388, 1995.
28. Nolan, A. "The Determinants of Urban Households' Transport Decision: a Microeconomic Study Using Irish Data." Presentation to the 7th Spring Meeting of Young Economists, Paris, France, 2002.
29. Anastasopoulos, P.C., A.P. Tarko, and F.L. Mannering. "Tobit Analysis of Vehicle Accident Rates on Interstate Highways." *Accident Analysis and Prevention*, Vol. 40, pp. 768-775, 2008.
30. Scheraga, C.A. "Operational Efficiency Versus Financial Mobility in the Global Airline Industry: a Data Envelopment and Tobit Analysis." *Transportation Research Part A*, Vol. 38, pp. 383-404, 2004.
31. Garcia Sanchez, I.M. "Technical and Scale Efficiency in Spanish Urban Transport: Estimating with Data Envelopment Analysis." *Advances in Operations Research*, Article ID 721279, 2009.

32. Maddala, G.S., *Limited-dependent and Qualitative Variables in Econometrics*. Cambridge University Press, New York, 1983.
33. Wohl, M. and C. Hendrickson. "Transportation Investment and Pricing Principles." John Wiley and Sons, 1985.
34. Muraleetharan, T., K. Meguro, T. Adachi, T. Hagiwara, and S. Kagaya. "Influence of Winter Road Conditions and Signal Delay on Pedestrian Route Choice in Japan's Snowiest Metropolis." In *Transportation Research Record No. 1939*, pp. 145-153, Transportation Research Board of the National Academies, Washington, D.C., 2005.
35. Morgan, J.T. and J.D.C. Little. "Synchronizing Traffic Signals for Maximal Bandwidth." *Operations Research*, Vol. 12, pp. 896-912, 1964.
36. Little, J.D.C., M.D. Kelson, and N.H. Gartner. "MAXBAND: A Program for Setting Signals on Arteries and Triangular Networks." *Transportation Research Record No. 795*, TRB, National Research Council, Washington, DC, pp. 40-46, 1981.
37. Messer, C.J., R.H. Whitson, C.L. Dudek, and E.J. Romano. "A Variable Sequence Multiphase Progression Optimization Program." *Highway Research Record No. 445*, pp. 24-33, 1973.
38. Messer, C.J., H.E. Haenel, and E.A. Koeppe. "A Report on the User's Manual for Progression Analysis and Signal System Evaluation Routine—Passer II." Texas Transportation Institute Report No. TTI-218-72-165-14, Texas Transportation Institute, Texas A&M University, College Station, TX, 1974.
39. Gartner, N.H., S.F. Assmann, F. Lasaga, and D.L. Hou. "MULTIBAND – A Variable-Bandwidth Arterial Progression Scheme." *Transportation Research Record No. 1287*, pp. 212-222, 1990.
40. Tsay, H.-S. and L.-T. Lin. "A New Algorithm for Solving the Maximum Progression Bandwidth." In *Transportation Research Record No. 1194*, pp. 15-30, 1988.
41. Yin, Y., M. Li, and A. Skabardonis. "Offline Offset Refiner for Coordinated Actuated Signal Control Systems." *ASCE Journal of Transportation Engineering*, Vol. 133, No. 7, pp. 423-432, 2007.
42. Hillier, J.A. and R. Rothery. "The Synchronization of Traffic Signals for Minimum Delay." *Transportation Science*, Vol. 1, pp. 81-94, 1967.
43. Hillier, J.A. "Appendix to Glasgow's Experiment in Area Traffic Control." *Traffic Engineering and Control*, Vol. 7, No. 9, 1966.
44. Robertson, D.I. " 'TRANSYT' Method for Area Traffic Control." *Traffic Engineering and Control*, Vol. 11, pp. 276-281, 1969.
45. Abbas, M., D. Bullock, and L. Head. "Real-Time Offset Transitioning Algorithm for Coordinating Traffic Signals." In *Transportation Research Record No. 1748*, Transportation Research Board of the National Academies, Washington, DC, pp. 26-39, 2002.
46. Luyanda, F., D. Gettman, L. Head, S. Shelby, D. Bullock, and P. Mirchandani. "ACS-Lite Algorithmic Architecture: Applying Adaptive Control System Technology to Closed-Loop Systems." In *Transportation Research Record No. 1856*, Transportation Research Board of the National Academies, Washington, DC, pp. 175-184, 2003.
47. Gettman, D., S.G. Shelby, L. Head, D. Bullock, and N. Soyke. "Data-Driven Algorithms for Real-Time Adaptive Tuning of Offsets in Coordinated Traffic Signal Systems." In *Transportation Research Record No. 2035*, Transportation Research Board of the National Academies, Washington, DC, pp. 1-9, 2007.
48. Day, C.M. *Performance-Based Management of Arterial Traffic Signal Systems*. PhD Thesis, Purdue University, May 2010.
49. Day, C.M., and Bullock, D.M. *Arterial Performance Measures, Volume 1: Performance-Based Management of Arterial Traffic Signal Systems*. NCHRP 3-79A Report, National Cooperative

- Highway Research Program, Transportation Research Board, Washington, DC, under review, to appear 2010.
50. Day, C.M., E.J. Smaglik, D.M. Bullock, and J.R. Sturdevant, (2008). "Quantitative Evaluation of Actuated Coordinated Versus Nonactuated Coordinated Phases," *Transportation Research Record No. 2080*, TRB, National Research Council, Washington, D.C., pp. 8-21.
 51. Day, C.M. and D.M. Bullock. "Evaluation of Alternative Algorithms for Traffic Signal Offset Optimization Using High Resolution Event Data." Submitted to *Transportation Research Record*, July 31, 2010.
 52. Smaglik, E.J., Sharma, A., Bullock, D.M., Sturdevant, J.R., and Duncan, G. "Event-Based Data Collection for Generating Actuated Controller Performance Measures." *Transportation Research Record No. 2035*, Transportation Research Board of the National Academies, Washington, DC, pp. 97-106, 2007.
 53. Wasson, J.S., J.R. Sturdevant, D.M. Bullock, "Real-Time Travel Time Estimates Using MAC Address Matching," *Institute of Transportation Engineers Journal*, ITE, Vol. 78, No. 6, pp. 20-23, June 2008.
 54. Schrank, D., and T. Lomax, The 2009 Urban Mobility Report. Texas Transportation Institute, July, 2009.
 55. "Analysis of Costs from Idling and Parasitic Devices for Heavy Duty Trucks," Technology and Maintenance Council Recommended Practice Bulletin 1108. Issued March 1995, reprinted 2003 by TMC/ATA.
 56. Lutsey, N.P., J.P. Wallace, C.J. Brodrick, H.A. Dwyer, and D. Sperling, "Modeling Auxiliary Power Options for Heavy-Duty Trucks: Engine Idling vs. Fuel Cells." Society of Automotive Engineers Report No. 2004-01-1479, October 2004.
 57. Emission Facts: Greenhouse Gas Emissions from a Typical Passenger Vehicle EPA420-F-05-004 February 2005, <http://www.epa.gov/OMS/climate/420f05004.htm>, Accessed July 27, 2010.
 58. EPA Analysis of the American Clean Energy and Security Act of 2009 , H.R. 2454 in the 111th Congress, http://www.epa.gov/climatechange/economics/pdfs/HR2454_Analysis.pdf Accessed July 27, 2010.