Advanced Traffic Signal Control

Using Bluetooth Detectors

by

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Author’s Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Some of the material in this thesis has already been published and/or presented at a conference. These publications are outlined below:

1. "Advanced Traffic Signal Control using Bluetooth/Wi-Fi Detectors". CITE Annual Meeting and Conference 2016. Kelowna, BC, Canada (June 2016).

   <u>Authors</u>

   Hart-Bishop, Jordan

   Zarinbal, Amir (PhD Candidate)

   Hellinga, Bruce (Research Supervisor)

   <u>Sections Covered</u>

   Chapter 3 Section 3.1.2 outlines the Bluetooth simulation software package developed by Mr. Zarinbal, which was relied on in this thesis and the submitted publication to process the data produced by me through my simulation experiments. The simulated Bluetooth data presented in Chapter 4 and Chapter 6 were produced by the same software.
   The content in Chapter 3 Section 3.3 was developed by me under the supervision of Dr. Hellinga, as well as the Pilot Field Study presented in Chapter 5.

2. "Hespeler Road Corridor Traffic Management System: Using Bluetooth Detector Data to Identify Atypical Traffic Conditions for which Traffic Responsive Signal Control may be Beneficial". Internal Project Report, Waterloo, ON, Canada (January 2017)

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   <u>Sections Covered</u>

   Chapter 6 uses an algorithm developed by Dr. Hellinga that was produced using data summarized by Mr. Wang and Mr. Zarinbal. I assisted with the development and preliminary data processing of the pilot field study outlined in this thesis.

Abstract

Traditionally signal timing plans are developed for expected traffic demands at an intersection. This approach generally offers the best operation for typical conditions. However, when variation in the traffic demand occurs, the signal timing plan developed for typical conditions may not be adequate resulting in significant congestion and delay. There have been many techniques developed to address these variations and they fall into one of two categories: (1) if the variations follow a consistent temporal pattern, then a set of fixed-time signal timing plans can be developed, each for a specific time of the day; (2) if the variations cannot be predicted *a priori*, then a system that measures traffic demands and alters signal timings in real-time is desired. This research focuses on improving the latter approach with a novel application of Bluetooth detector data.

Conventional traffic responsive plan selection (TRPS) systems rely extensively on traffic sensors (typically loop detectors or equivalent) to operate, which are costly to install and maintain, and provide information about traffic only at the points which they are installed. This thesis explores the use of Bluetooth detectors as an alternative data source for TRPS due to their ease of installation and capability to provide information over an area rather than at a single point.

This research consists of simulated and field traffic data associated with Bluetooth detectors. The field and simulated traffic data were from a section of Hespeler Road in Cambridge Ontario, bounded by Ontario Highway 401 to the north and Highway 8 to the south. The study corridor is approximately 5.0 kilometres long, and consists of 14 signalized intersections.

In order to determine the potential of Bluetooth detectors as a data source, several measures of performance were considered for use in a Bluetooth-based system. The viability of each one was assessed in microsimulation experiments, and it was found that Bluetooth travel time was the most accurate at identifying true traffic conditions.

On the basis of the simulation results a field pilot study was designed. Bluetooth detectors and conventional traffic detectors were installed at study intersections along the Hespeler Road corridor to measure real traffic conditions. From these measurements an algorithm was developed to determine when traffic conditions varied from the expected conditions.

The final stage of the research evaluated the proposed algorithm using a controlled simulation environment with known atypical traffic patterns. It was found that the algorithm was capable of identifying the atypical conditions that were simulated based on field conditions.

The key findings of this research are that (1) Bluetooth detectors are able to provide measured travel times from individual vehicles with sufficient accuracy, and with sufficient sample sizes, that the aggregated travel time information can be used to identify the traffic conditions at a signalized intersections; and (2) these measurements can be used instead of data from conventional traffic detectors, to determine when to switch from time of day fixed time traffic signal control to TRPS control.

Acknowledgments

I would like to thank Dr. Bruce Hellinga for his support and guidance in the completion of this thesis. His input and technical insight were invaluable for the completion of this thesis and the beginning of my career in traffic engineering.

My fellow students in my research group, Wenfu Wang, Cameron Berko, and Amir Zarinbal allowed for me to complete this thesis through their assistance, guidance, and willingness to discuss ideas.

I would like to thank my fellow graduate student and friend Joseph Stoner for his friendship and guidance throughout my time at Waterloo and beyond. You showed me how hard work and a willingness to help others can have a positive result on your community.

My family provided limitless support during the completion of my thesis. I greatly appreciated always having a place to call home and home cooked meals from my parents when I was at my busiest. My brother, Mathew, was always willing to offer me another perspective which helped me with my degree and beyond.

Finally, I would like to thank my wife, Caitlyn, for her love and support on this chapter of our life together. Her support kept me motivated throughout my thesis and I look forward to our future together.

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1.0 Introduction

Inefficiencies at signalized intersections can result in significant congestion on urban arterial road networks and consequently are responsible for a significant fraction of the delay, fuel consumption, and tail pipe emissions (iTRANS, 2006). When traffic demands remain constant over time, optimal signal timing plans can be developed off-line and implemented. However, traffic demands almost always exhibit variations over time. There has been many studies into ways to deal with these variations, with solutions of varying complexity and expense. Essentially, these methods can be classified into two approaches.

One approach has been to make the assumption that these variations follow a consistent pattern such that they can be predicted based on the day of the week and the time of day. Under this assumption, it is possible to develop different signal timings for different time periods of the day (and different days of the week) and for each time period, implement signal timing that are optimized for the anticipated traffic demands.

The other approach focuses on developing systems that can measure the traffic demand in real-time and then use this information to update the signal timing plans. However, these systems require the installation and maintenance of dedicated traffic sensors along the arterial corridor making these systems more costly.

Inductive loop detectors are traditionally used to provide information to traffic signal controllers. Loops are able to measure the presence of a vehicle as it passes over the detector and as such can directly measure traffic volume. Typically, the objective of traffic signal control is to minimize vehicle delay. Loop detectors, and other similar traffic sensor technologies, are not able to measure delay. Consequently, it is necessary to use models to estimate delay as a function of the measured traffic volumes.

The use of Bluetooth detectors as a data source is a recent development within the field of traffic engineering (Quayle et al., 2010). Unlike loop detectors, Bluetooth detectors provide the ability to directly measure travel times of vehicles in the traffic stream. In addition, Bluetooth detectors have the potential to be a lower cost option than the other existing tools primarily due to their ease of installation and maintenance.

This thesis explores a potential use of Bluetooth detectors as a data source for traffic signal control systems. This research aims to provide transportation engineers with another tool to improve signalized intersection performance, particularly along arterial corridors that experience substantial variations in traffic demands.

1.1 Background

Traffic control has long been studied at intersections to increase the operating capacity and encourage safe and efficient movement of vehicles and persons. Various strategies have been developed to address the problem of conflicting traffic movements, and advances in technology allows for more robust solutions. Of primary focus has been to modify the signal timing plans in response to the demand at a given intersection.

One such strategy, Traffic Responsive Plan Selection (TRPS) has long been a tool available to traffic engineers as a way to reduce congestion at traffic signals. However, despite its long history, other forms of signal control are often selected over this technique (Abbas and Abdelaziz, 2009). This section identifies the traditional types of traffic signal control, and provides some clarification regarding the terminology that is used in this thesis. In addition, the section also presents a brief overview of Bluetooth detectors and their recent adoption as a traffic measurement sensor.

1.1.1 Types of Signalized Control

Traffic signals can be seen at their core as tools to allocate capacity to conflicting traffic movements in a safe and orderly manner. In their simplest form they allocate green and red time to traffic in a pre-determined cycle. However, traffic signals have been increasing in complexity and scope in recent times. In fact, there is now some confusion involved when defining types of signalized control. For example, when using the term “traffic responsive” *The Traffic Signal Timing Manual* (2008) and the *Traffic Control System Handbook* (2005) have two different definitions of traffic responsive control. *The Traffic Signal Timing Manual* defines traffic responsive control as “utilizing a predetermined timing plan that best suits the current traffic conditions” (Koonce et al., 2008), this definition encompasses both time-of-day operation and TRPS. Conversely, the *Traffic Control System Handbook* defines traffic responsive control as “timing plans generated rapidly and automatically using system sensors”, (Gordon and Tighe, 2005). This definition would be considered as traffic adaptive control according to *The Traffic Signal Timing Manual* (2008) and by many professionals.

To reduce confusion the definitions used in *The Traffic Signal Timing Manual* (2008) are used. The types of signal operation are listed below:

- Pre-timed: One signal timing plan is created and repeated at an intersection with no response to traffic conditions.
- Time-of-Day: Several signal timing plans (3-5) are developed based on predicted traffic flows and selected by the traffic signal controller based on the day of week and time. The signal controller cannot respond to actual changes in traffic conditions (beyond actuation).
- Traffic Responsive Plan Selection (TRPS): A number of signal timing plans are developed based on a predetermined set of traffic conditions. The system monitors traffic conditions using dedicated traffic sensors (typically in 15-minute intervals) and changes to a more suitable signal plan, if required.
- Adaptive Traffic Signal Control: Signal timing plans are not developed in the traditional sense, but rather control algorithms are implemented by the traffic signal controller to respond to changing traffic conditions in real-time. This technique is heavily dependent on extensive traffic detection systems.

The technique that is of greatest interest for this research is TRPS, as when properly configured, it can greatly reduce the delay experienced at traffic signals by an unexpected change in demand (Abbas and Abdelaziz, 2009).

Based on this review there are several challenges with implementing a TRPS systems, first is the development and implementation of the traffic signal library. Second is identifying when the traffic conditions can no longer be adequately served by the current plan. Finally, the logic to select an appropriate plan based on the change in traffic conditions can be difficult. This is due to the fact that the data from conventional loop detector systems require a significant amount interpretation for use in determining the traffic conditions and then selecting an appropriate plan. This thesis primarily focuses on the second challenge, of using a novel detection technology to identify these shifts in traffic.

1.1.2 Bluetooth Detectors

As introduced above, Bluetooth detectors have increased in popularity as a source of travel time data in recent years. The measurements are obtained from matching timestamps from Bluetooth detectors based on unique media access control addresses (MAC address) associated with Bluetooth devices. The matching process usually takes place between two detectors and is illustrated in **Figure 1-1**.

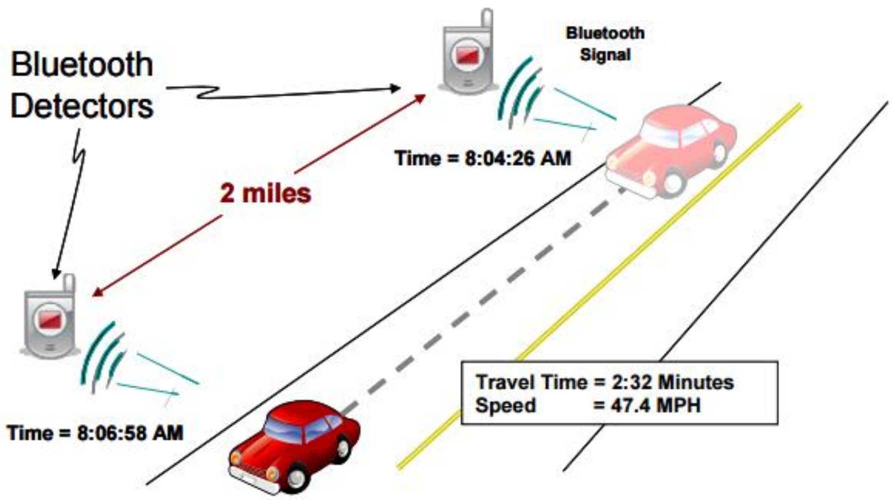

Figure 1-1: Visualization of Bluetooth travel time calculation (Haghani et al., 2008)

In their most simple application Bluetooth detectors can be used to collect and store travel times along a corridor to assess the performance of a corridor. They can also be used to provide real-time delay estimations to transportation officials or the general public. This research seeks to expand their use in their real-time application for the use in traffic signal control.

1.2 Problem Statement

This research seeks to address the limitations imposed by the use of loop detectors as a point data source that acts as a surrogate for delay. The goal of the research is to improve intersection control by utilizing measurements from Bluetooth detectors instead of loops. When using conventional systems, volume and occupancy are used to estimate delays. With Bluetooth sensors, travel times can be directly measured and then used to estimate delays. The purpose of the thesis is to investigate to what extent this can be used to improve signal control, and specifically traffic responsive signal control.

1.3 Research Objectives

This research aims to explore the problem statement above by determining the viability of Bluetooth detectors as a means to modify traffic signal timings. The main objectives of this research are:

(1) To determine which Bluetooth data can be used to measure arterial traffic conditions accurately through simulation;
(2) Assess if the Bluetooth data can be used to identify atypical traffic conditions associated with increased delays; and
(3) Assess the potential of these data to improve signal timing plans in real-time.

1.4 Thesis Organization

This thesis is organized as follows:

- Chapter 2 summarizes the existing literature related to the research.
- Chapter 3 presents the simulation resources and experiment methodology.
- Chapter 4 outlines the results of the simulation experiments.
- Chapter 5 presents the pilot field study and data collected over the duration of the pilot study.
- Chapter 6 assesses the algorithm derived from the field data to determine the viability of Bluetooth detectors as a data source for TRPS.
- Chapter 7 summarizes the conclusions and recommendations as a result of this research.

2.0 Literature Review

This chapter examines the current state of research when it comes to the use of Traffic Responsive Plan Selection signal control systems and the use of Bluetooth detectors as a data source for traffic information, in particular their recent use on arterial roadways.

2.1 Overview

As presented in Chapter 1, Traffic Responsive Plan Selection traffic signal control is an established, but uncommon, mode of signal control. Defined as the halfway point between static time-of-day and fully adaptive plans, there has been some success in implementing them in the past (Abbas and Abdelaziz, 2009). However, the data requirements and plan development process can be quite onerous due to the nature of the data source (loop detectors) providing point information which is then extrapolated to traffic conditions. The challenge with developing the controller rules is seen as a barrier to TRPS that this research aims to address with Bluetooth data.

Over the last decade, Bluetooth detectors have increased in popularity as a data source for freeway, and recently, arterial travel times. Due to the growing popularity of Bluetooth-enabled devices, they continue to be a promising source of travel time data, with recent projects attempting to expand the use of Bluetooth detectors to include real-time O-D surveys (Barcelo et al., 2010). This research seeks to expand their use further by examining their potential as data source for TRPS signal control.

2.2 Traffic Responsive Plan Selection Signal

The technique that is of greatest interest for this thesis is TRPS, as when properly configured, it can greatly reduce the delay experienced at traffic signals by an unexpected change in demand (Abbas and Abdelaziz, 2009). The system accomplishes this by monitoring traffic conditions in a close to real-time algorithm that selects an appropriate signal timing from a pre-defined library of signal timings if certain conditions are met.

To identify which timing is the most appropriate from the library of plans TRPS signal control utilizes detectors which collect occupancy and count data from the network surrounding a traffic signal. This information is then scaled and weighted by the traffic controller to generate Computational Channel (CC) parameters. The CC parameters are then combined to produce the Pattern Selection (PS) parameter, which is used by the controller to determine if the current plan should be switched to another plan (Abbas and Sharma, 2004). The scaling, weighting, CC parameters, and PS parameters vary by the signal controller manufacturer, however the general process is consistent between them (Balke et al., 1997). According to the *Guidelines for implementing traffic responsive mode in TxDOT closed-loop traffic signal systems* (1997) the following are the main steps to implement TRPS:

1. Assign system detectors: Traditionally loop or video detectors are used to determine the following information about the traffic on the network:
    - An increase or decrease in traffic demand - these changes may result in a change to cycle length,
    - Change in directional demand - changes may result in a change to the offset, and
    - Change in cross-street demand - changes may result in a change to the green split.

    Note that although the above indicate a change in one aspect of the signal timing plan, there is no modification made to the signal timing plans from the library of plans available, one signal plan may address several scenarios at once.
2. Collect volume and occupancy data: This information should be collected from the identified system detectors for a minimum of two weeks to allow for daily and weekly trends be identified.
3. Identify Control Conditions: After processing the traffic data, there should be patterns that are apparent, and an engineer can identify which traffic conditions may require different signal plans (cycle, offset, and splits). Additionally, any special circumstances, such as special events or traffic increase due to diversion should be considered at this step.
4. Develop Timing Plans: The control patterns identified in Step 3, along with the traffic data from Step 2 are used with traffic signal timing software to assist with the development of traffic signal plans for each of the identified conditions. These timing plans make up the initial library of signal timing plans. This initial set of plans may be reduced as a result of the following steps.

5. Determine Scaling Factors: The measurements from the on-street sensors are scaled before being converted into a set of parameter values. The volume data are typically scaled by dividing the measured volume by the saturation flow rate of the lane from which the measurements were taken. The occupancy data are typically scaled by dividing the measured occupancy by a value of 25%, as this value typically corresponds to the onset of congestion.
6. Establish smoothing factors: The selection of smoothing factors allows for some tuning of the sensitivity of the system to changing traffic conditions. The exact tuning process differs by manufacture, but it is typically some form of weighted average between the current and previous periods.
7. Determine Weighting Factors: The weighting factors are another tool that can be used to tune the system by increasing or decreasing the importance level of the volume and/or occupancy of a particular system detector when computing the selection parameters.
8. Determine Thresholds: Selecting what values of the parameters will force the signal controller to adopt a different timing plan. There are typically two thresholds for each PS parameter, the value to increase the cycle length/offset/split and the value to decrease the cycle length/offset/split.
9. Fine-Tune Thresholds: Once the system is implemented it should be observed for at least two weeks to ensure that the transitions between signal plans is appropriate and not increasing delay.

Of particular importance for the operation of TRPS signal control is the location of detectors. The strategy for locating detectors has been a significant area of research and several procedures have been developed and refined (Kay et al., 1975), (Woods and Rowan, 1995). There has also been significant work on identifying which PS parameters should be used and how they should be calculated (scaling, weighting, and smoothing factors) for improved system performance (Abbas et al., 2004). Finally, a framework has been proposed to assist with evaluating the impact of TRPS by objectively determining the improvements made to the network (Nelson et al., 2000). Although the area of research is quite robust, due to the perceived complexity of implementing TRPS, the technique is not commonly used, despite its advantages over Time of Day (TOD) operation.

From the review of the literature it appears that the primary difficulties with developing and implementing TRPS signal control is centered on the detectors, for both the location and interpretation of their measurements. Thus when addressing potential improvements to TRPS signal control, the detector technology was selected as the starting point.

Bluetooth detectors may be able to act as system detectors instead of the conventional loop or video systems. This offers some unique opportunities, as unlike loop detectors, Bluetooth Detectors are not fixed and can be moved readily (assuming a power source is available). This mobility can make the placement of system detectors more forgiving (as once loops are installed in the pavement they are costly to relocate), allowing for the detector position to be varied as an additional way to tune the system. In addition, the detection radius of Bluetooth detectors enable the possibility of greater flexibility for the system, as loop or video detectors typically only give information about a limited point on the approach. If traffic is congested to the point where it does not extend past the static loop detector, sub-optimal conditions will take longer to identify. This would be eliminated with Bluetooth detectors as they operate with a wider zone.

However, there are some challenges that are presented by using Bluetooth detectors, and that is the measurements of traffic conditions are different than conventional systems. Rather than measuring volume and occupancy, Bluetooth detectors can measure travel times (both between and within a detector zone) of Bluetooth enabled vehicles. This difference will likely result in the scaling and weighting steps changing, as the travel time data is quite different than the count data. This may require a special system to simulate the traditional values to the traffic signal controllers.

2.3 Bluetooth Detectors

The increase in popularity of connected devices, and the ways that they communicate with each other resulted in a new data set for traffic engineers to consider when trying to measure the performance of a roadway or network. As presented previously, there has been significant progress in harnessing this latent information within road networks.

There has been significant efforts to use Bluetooth detectors as a source of travel time estimates on transportation facilities, in particular freeways (Hu, 2013). Freeways are an excellent facility for the application of this technology as they are relatively isolated from other sources of data and have limited access and egress points. The advantage that limited access and egress points provide are:

- The ability to restrict or completely remove differing paths between two Bluetooth detectors;
- Further to this point, vehicles on the freeway are in a closed system where all of the travel time is directly resultant from the travel between two points; and
- The high volume on freeways during the peak hours result in a significant pool of vehicles to act as potential probe vehicles.

Hu (2013) focused on the reliability of travel time predictions using Bluetooth detectors on freeways, and along with the research there has been practical application of the technology to provide real-time travel time information to drivers (City of Calgary, 2017).The application of the detectors shows that there is support from public agencies for the adoption of this technology.

Beyond the application of Bluetooth detectors on freeways, there has been progress in the application of Bluetooth detectors on urban arterials. A sample arterial road study of Spring Street in Atlanta, Georgia by Vo (2011) found that there was potential to use these data as a source of travel time information to a high degree of accuracy. Moghaddam and Hellinga (2013a) evaluated the application of algorithms that could reduce the impact of the following outliers that have been historically associated with non-freeway Bluetooth measurements:

- Stops along the travel route not associated with congestion;
- Non-auto trips (i.e. pedestrians); and
- Multiple devices in a single vehicle, due to the presence of bus routes.

It was found that it is possible to identify and minimize the impact that these outliers have further increasing the usefulness of Bluetooth data’s application in urban environments.

In addition to identification and minimizing the impact of outliers, Moghaddam and Hellinga (2013b) identified the magnitude of the detection and travel time measurement errors for Bluetooth travel times on arterial corridors. The study found that these errors can be modeled, further increasing the understanding of the use of Bluetooth detectors on arterial roadways.

Finally, Moghaddam and Hellinga (2014) explored the use of Bluetooth detectors for predicting near-future travel times on arterial roadways, similar to work that had been previously completed for freeways. It found that there was potential to get accurate predictions of travel time using real-time Bluetooth data.

The previous research involving Bluetooth detectors and their use on arterial roadways shows that they have significant promise as a reliable and accurate source of measured travel times. The ease at which this high quality data can be collected has resulted in a drastic expansion of their use in recent years. Haghani and Hamedi (2013) reviewed the current use of Bluetooth detectors in traffic detection, surveillance, and management and found that there are several emerging applications of Bluetooth detectors. However, at this time the application of using the measured travel times as an input into a traffic signal selection plan has not been explored in great detail. Recently, Zarinbal (2017) has developed a framework to estimate offsets using the Bluetooth travel time to a great degree of success using simulated data.

Therefore, this research seeks to expand the use of Bluetooth detectors as a data source for traffic signal timing plan selection. They are seen as an excellent candidate due to the aforementioned studies which outline the significant data requirements for TRPS signal systems and the relative strength of Bluetooth detectors as a traffic data source. Furthermore, increasingly municipalities are deploying Bluetooth detectors to obtain travel time information for network monitoring and for traveler information systems, providing an opportunity to leverage this investment by also using the Bluetooth data for improving traffic signal control. Examining the relationship between Bluetooth measurements and the traffic conditions could result in simplifying the detector requirements for TRPS by providing a direct measurement and response to travel times experienced by vehicles travelling on urban arterials.

3.0 Simulation Framework and Methodology to Assess Bluetooth Detectors use in Traffic Signal Control

This chapter describes the methods used to identify and assess the use of Bluetooth detectors as a viable data source for TRPS signal control. Due to the fact that the use of Bluetooth detectors as an input data source for signal controllers is a novel application of this technology, both simulation experiments and pilot field studies were conducted to establish the potential measurements and accuracy of these measurements.

The experiments that were conducted for this research are summarized in the flowchart on the following page (**Figure 3-1**).

The results from Experiments 1 and 2 are described in Chapter 4.0. The results from Experiment 3, the field study, are provided in Chapter 5.0. The results from Experiment 4 are provided in Chapter 6.

This chapter describes the tools, methodologies, and concepts that are common to all of the experiments. This chapter is organized as follows: Section 3.1 describes the traffic and Bluetooth data simulation software used for the simulation experiments. The study network for the simulation and pilot field project is described in Section 3.2. Finally, the candidate list of Bluetooth and true network Measures of Performance (MOPs) is presented in Section 3.3.

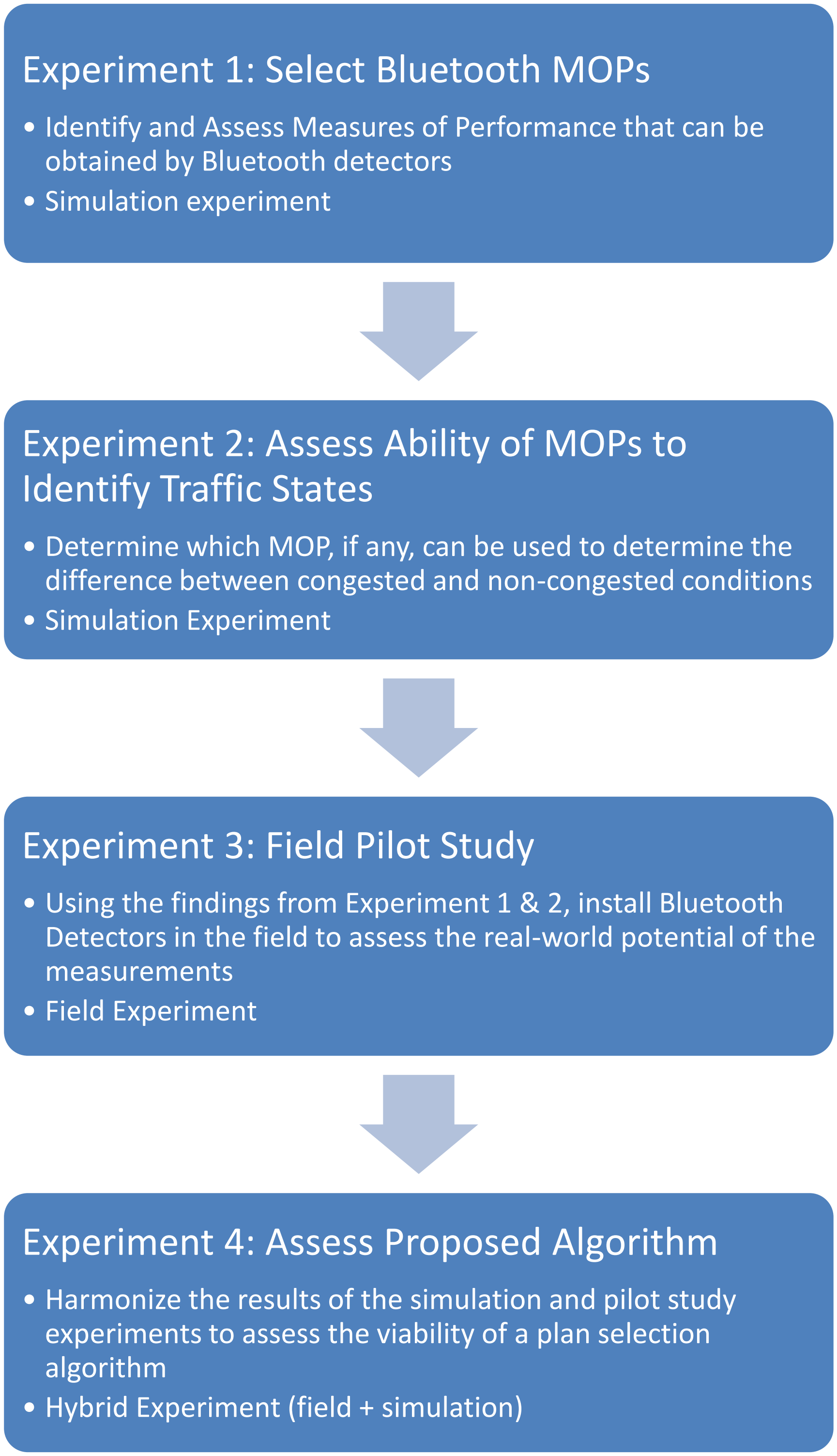

Figure 3-1: Research methodology flowchart

3.1 Simulation Tools

To assess the potential of Bluetooth measurements to identify traffic states, it was necessary to simulate both traffic data and Bluetooth detector data. This was accomplished by the use of two simulation software tools, namely the commercial traffic microsimulation software Vissim release version 7 (henceforth "Vissim") produced by PTV and the Bluetooth detection simulation software entitled BlueSynthesizer developed by Amir Zarinbal (2017) at the University of Waterloo. The relevant characteristics of these two software tools are described in the next sections.

3.1.1 Vissim 7: Traffic Microsimulation Software

Microsimulation models consider every network user as an individual unit, using car-following models and other similar models to determine the actions of each user every small time step (typically on the order of every 0.1 to 0.5 seconds).

Vissim was selected as the microscopic traffic simulation software for this thesis. Vissim is capable of modelling the behaviour of private vehicles, heavy vehicles, public transit, and pedestrian traffic. The simulations in Vissim include a graphical component, through which users can observe and interact with the simulation in real-time. This feature allows users to confirm that vehicles are modelled in a way that would match their expectations; **Figure 3-2** shows a sample of a signalized intersection, Hespeler Road at Eagle and Pinebush, in Vissim. The graphical interface depicts individual vehicles (scaled to their length), traffic signal head status, location of detectors, lane configuration, etc.

In order to create a microsimulation model, the network or intersection that is being modelled must be well defined. The key items that are required to define the network are: (1) the network geometry, (2) traffic signal timings, and (3) the traffic demand. Vissim has several models for the behaviour of vehicles, and as such these are not required inputs, but can be modified as part of the calibration process. The network geometry is modelled by mapping links on top of an aerial image of the network, which ensures the correct lane configuration and geometry. The traffic signal timings can be entered directly or can be imported from other software including Synchro Studios, which is commonly used to create and save signal timings. The traffic demand can be either estimated or obtained from turning moving counts of the network.

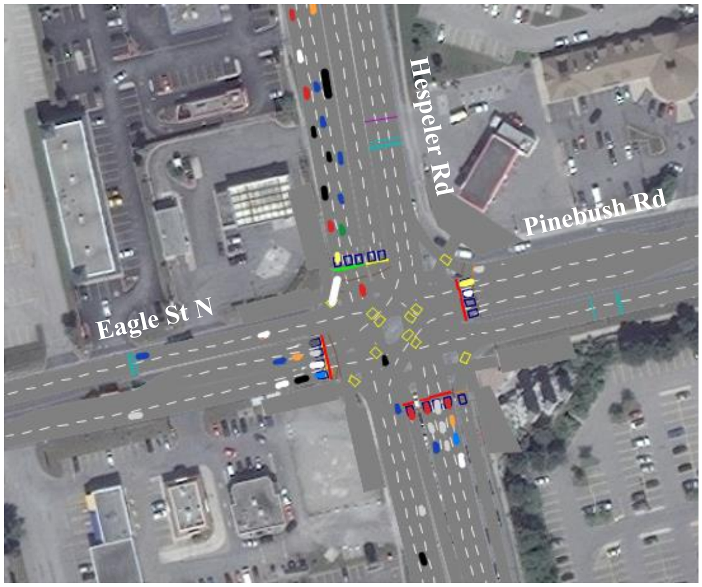

Figure 3-2: Screenshot of Vissim 7 simulation display (Background image from Bing Maps)

Vissim is capable of providing a large amount of information about many aspects of the simulated network. This information includes network level statistics such as average vehicle delay; road section data such as individual vehicle or aggregated travel times between designated locations; traffic sensor data such as loop detector outputs; signalized approach measures such as average or maximum queue lengths; and data from individual vehicles, including complete vehicle trajectories. The vehicle trajectories consist of the vehicle location and speed at every simulation step. These high-resolution data are analogous to having perfect GPS data for all vehicles in the network every 0.1 second (this value can change depending on the size of the simulation step). Vissim cannot directly model Bluetooth detectors. However, a separate software tool was used to model the generation of Bluetooth detector data as described in the next section. This software is used in combination with the Vissim software to provide an off-line evaluation platform of Bluetooth detectors.

3.1.2 BlueSynthesizer: Bluetooth Data Simulation Software

A detailed description of this software is available in the literature (Zarinbal, 2017). This section provides a brief summary of the software and how it is used within the research described by this thesis.

As described previously, Vissim has no in-software capability to simulate Bluetooth detections or to generate the data that would be provided by Bluetooth detectors. However, the vehicle trajectory files generated as an output of the simulation software are incredibly valuable as a starting point for understanding how a vehicle can be measured with Bluetooth detection. The location and time of detection of a Bluetooth device is highly dependent on the pattern of the vehicle trajectory which is a function of the traffic characteristics and the interaction of Bluetooth detectors and Bluetooth devices.

BlueSynthesizer utilizes Vissim trajectory files from a base group of sample vehicles as candidates for detection in a variety of signal control and traffic conditions. The software then generates Bluetooth hits and detection records similar to the process that would occur with a deployed Bluetooth detector. **Figure 3-3** shows a screenshot of the developed software, which shows the functionality of the software, which are outlined below:

- Bluetooth Settings: Used to select the parameters for the virtual detectors and traffic stream (for example level of market penetration);
- Detectors: The location and number of simulated detectors, referenced to the Vissim coordinate system;
- Offline Simulation: The main function used within this research, parses Vissim trajectory files along with detector settings to create a database of simulated Bluetooth data;
- Multi-Run and Signal Controller: Tools that are used to interact with Vissim parameters to assist in the generation of trajectory files; and
- Online Simulation: A feature to interact with Vissim in real time to generate Bluetooth detections and make these detections available in real-time. This feature was still in development at the time of this research and was not used in this research.

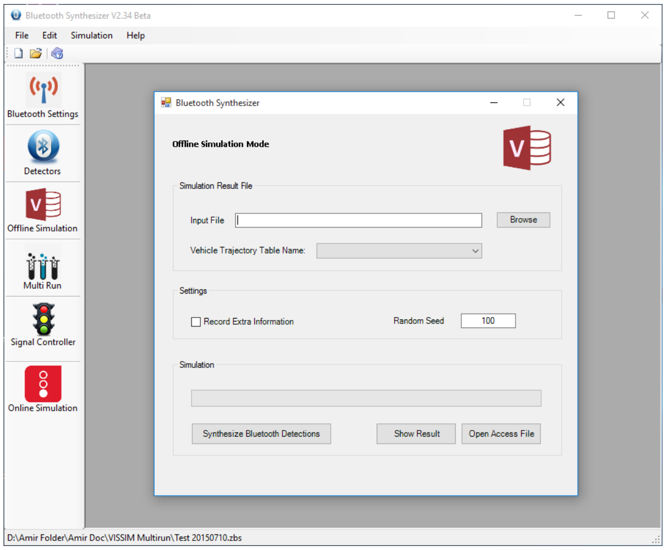

Figure 3-3: Screen capture of BlueSynthesizer (Hart-Bishop et al., 2016)

The Bluetooth simulation process randomly designates a subset of vehicle trajectories as Bluetooth enabled vehicles, based on the level of market penetration. At each scanning interval of the simulated Bluetooth detectors, the location of each individual Bluetooth enabled vehicle is extracted from the vehicle trajectory data. Using the location-based probability of detection, the software determines whether or not the vehicle is detected, and if detected, the time and location of each simulated Bluetooth detection is recorded in the output database. Note that the exact location of the hit is recorded for the purpose of validating the Bluetooth detection simulation and would not be an output of an actual Bluetooth detector.

In addition to the simulated data, the software captures a variety of other measurements to provide a measure of "truth" for the Bluetooth enabled vehicles. The times at which each vehicle entered the detection zone for each detector is recorded, along with when it passed the sensor, and exited the detection zone. Moreover, the location and time of the first and last Bluetooth hit is recorded. These data form a Bluetooth detection record, and are used to calculate the Bluetooth dwell time which was of particular interest for this research. **Figure 3-4** shows a sample of output charts from the software that shows a trajectory of the vehicles and location of Bluetooth hits as well as Bluetooth dwell time.

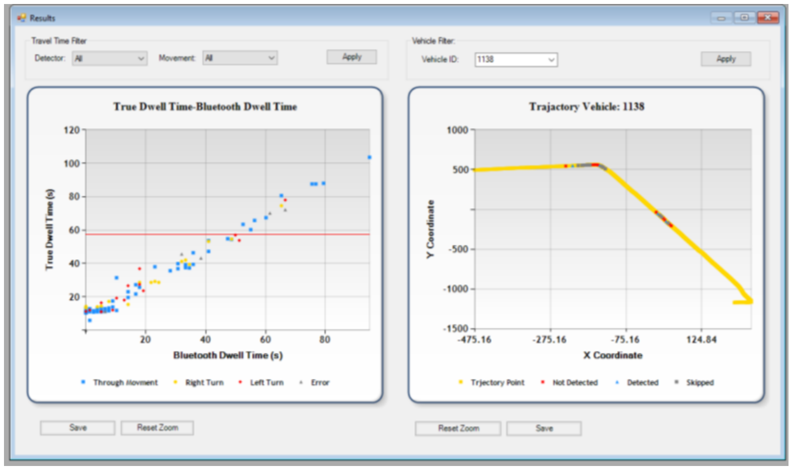

Figure 3-4: BlueSynthesizer sample output (Hart-Bishop et al. 2016)

Similar to an actual Bluetooth detector, travel time is calculated by the time difference of the matched MAC (in this case Vissim vehicle ID) at successive detectors and average speed is computed on the basis of the travel time and the distance between the successive detectors.

Providing the high quality Vissim trajectories and the Bluetooth settings allow for the software to simulate Bluetooth detectors and their associated data, as well as calculate the MOPs of interest for this research.

3.2 Study Network

This research was conducted as part of a larger project investigating novel methods of responsive signalized control along a real-world corridor in Cambridge, Ontario Canada in partnership with the Region of Waterloo. As such, there was a study corridor pre-selected for the simulation study, a section of Hespeler Road bounded by Ontario Highway 401 to the north and Highway 8 to the south. The study corridor is approximately 5.0 kilometres long, and consists of 14 signalized intersections. The corridor is bounded by a mix of uses including commercial, industrial, and residential.

This corridor was selected as the study candidate due to its proximity to Highway 401 and the variety of uses along its length. The study corridor can be seen in **Figure 3-5**. Of particular interest is the intersection of Hespeler Road and Eagle Street North / Pinebush Road ("Pinebush Road" for simplicity) as it handles high volumes and is immediately adjacent to the Highway 401 ramp terminal intersections.

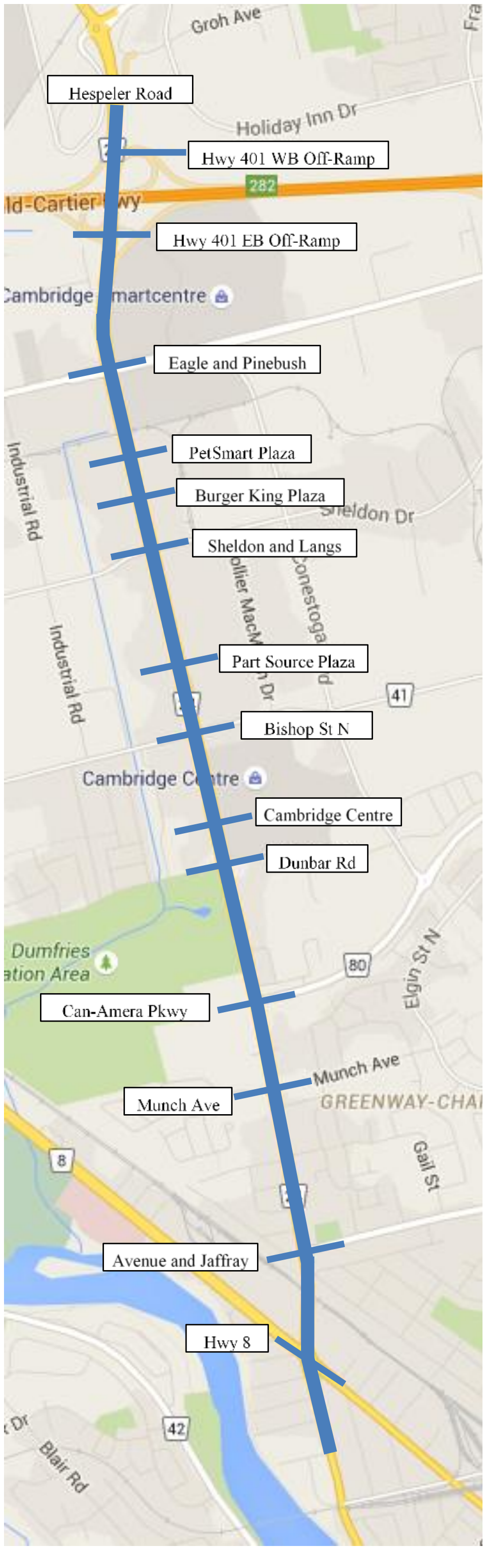

Figure 3-5: Outline of study corridor (Background image Google Maps)

This network was coded in Vissim. Aerial images were used to define network geometry. Turning Movement Counts (TMCs) and signal timing plans for each of the intersections along the corridor were obtained from the Region of Waterloo. Validation of the simulation output was conducted by comparing the turning movement counts at each simulated intersection to the TMCs obtained from the Region of Waterloo. This procedure is described in Error! Reference ource not found..

This simulation network was used as the foundation of the simulation experiments presented later in this thesis.

3.3 Proposed Measures of Performance

In order to establish a framework for TRPS signal control, there was a need to identify if Bluetooth detectors could provide real-time measurement(s) that could be used to assess the intersection performance. To this end, several Measures of Performance (MOPs) were identified as potential inputs to the TRPS signal control system. Bluetooth detectors are capable of supplying various data for analysis and use for traffic engineers. As previously presented, the primary use of Bluetooth data was to obtain an approximate travel time on a freeway or arterial corridor. This research examined this traditional measure, as well as several other measurements that could be obtained through the use of Bluetooth detectors and which are explored in the following sections.

One concept to establish before presenting the proposed MOPs is the difference between double detector versus single detector measurements. A double detector measurement requires a device's MAC ID to be detected at two separate Bluetooth detectors in order to be measured, whereas a single detector measurement can occur when a MAC ID is detected at least once at any Bluetooth detector. The difference between these two measurement types is important due to the concept of measurement lag which was explored in **Chapter 2.0**.

3.3.1 Bluetooth Travel Time

The first MOP that was considered as a candidate for TRPS is the Bluetooth Travel Time (TT_B). It was considered as the primary candidate for assessing the traffic conditions at an intersection as it is the conventional measurement that has been supplied by Bluetooth detector systems. This leads it to be an attractive choice for use, as many systems already exist that are capable of reporting these data. Travel time is a double detector measurement, as it is defined as the difference between the time of detection at an upstream Bluetooth detector and a downstream Bluetooth detector. It is typically calculated using the following formula:

TT_B = *Time of First Detection Downstream – Time of First Detection Upstream* **Equation 1**

Note that **Equation** 1 presents the first-first travel time, which is one of several ways to measure Bluetooth travel time. The term "first-first" is used as it relies on only the first detection of a Bluetooth device at each detector, and effectively ignores the other detections, if any. As it is possible for a device to be detected multiple times at a single detector there are several ways to define Bluetooth travel time, of which the common definitions are as follows:

- First-first;
- First-last;
- Last-last;
- Last-first;
- Average-last and
- Average-first.

First-first is typically used by Bluetooth detector vendors to measure travel time. The other methods listed above share the same pattern as first-first, for example first-last would look at the first detection of a device of an upstream detector, and the last detection of the downstream detector, ignoring all other points in between.

However, due to the application of using the Bluetooth detectors to inform traffic signal control, practical requirements (e.g. access to power and communications) often require that detectors be placed at an intersection. Thus travel times are expected to reflect the time taken by vehicles to travel from an upstream signalized intersection to the downstream signalized intersection. Vehicles frequently experience delay upstream of a signalized intersection due to the signal operations. This delay should be part of the measured travel time on the approach link. However, when assuming the upstream detector is located midblock and the downstream detector is located at the signalized intersection, the first-first travel time will likely underestimate the true travel time as vehicles are likely to be first detected by the downstream detector when they are still upstream of the stopline. This is illustrated in **Figure 3-6**, where a time-space diagram shows a single vehicle approaching a signalized intersection. The vehicle is first detected by the upstream detector well upstream of any impacts from the downstream traffic signal. As the vehicle approaches the downstream intersection, the signal switches to red and the vehicle is forced to decelerate and stop. Soon afterwards, the vehicle is first detected by the downstream detector. The vehicle is detected twice more before the signal turns green and the vehicle exits the downstream detection zone. It is clear that the first-first travel time under-estimates the true travel time because it does not capture all of the time that the vehicle is delayed at the traffic signal. In comparison, the first-last travel time does capture this delay and provides a travel time estimate much closer to the actual travel time that the vehicle experiences. Note that for this illustration the actual travel time is defined as the time when the vehicle first enters the upstream detection zone, to when it leaves the downstream zone.

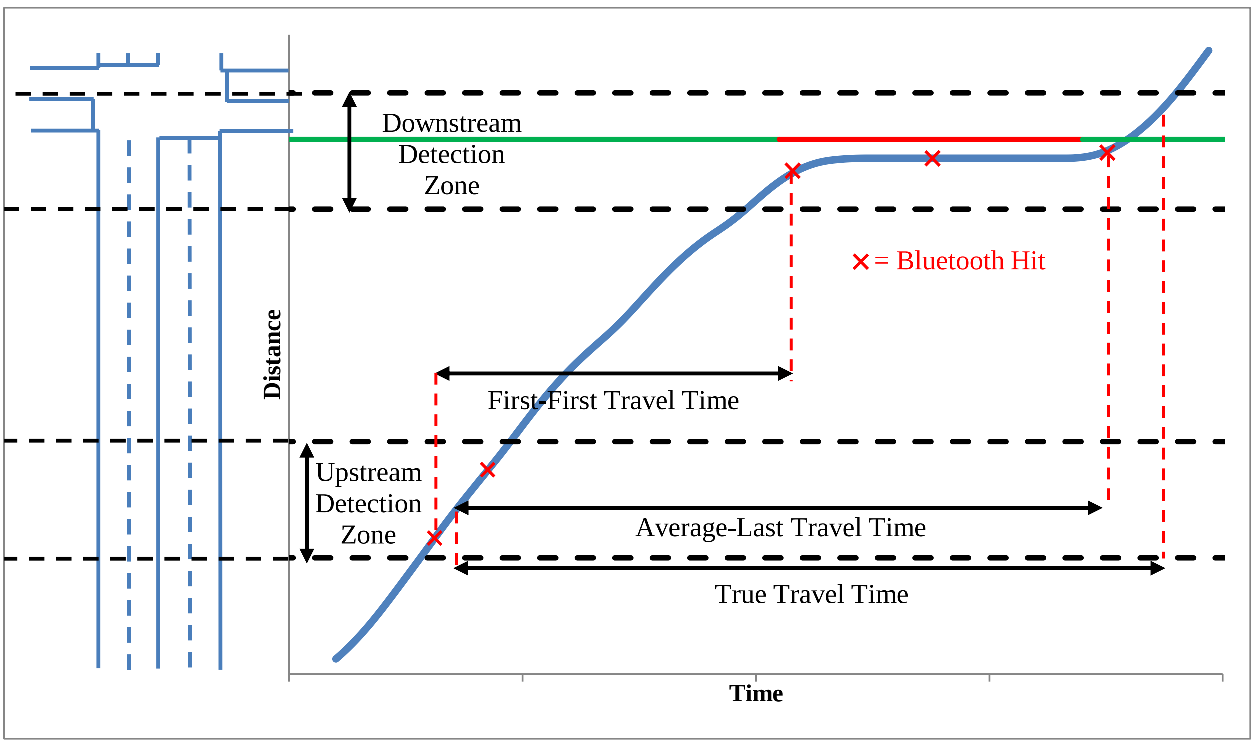

Figure 3-6: Comparison of Bluetooth travel times at a signalized intersection approach

As such, Experiment 1 examined the accuracy of several different travel time measurements for reflecting actual traffic conditions.

Travel time was selected as a potential MOP due to the fact that the calculation of travel time using Bluetooth detectors is very well understood and widely used. Additionally, travel time is strongly correlated with delay, and the minimization of delay is one of the main measures of signalized intersection performance. The ability to directly measure travel time via Bluetooth detectors may provide substantial benefits over traditional sensors which are typically only capable of measuring volumes. These two features make this a very strong candidate as a MOP to be used in the field.

3.3.2 Bluetooth Dwell Time

The next proposed MOP is the Bluetooth Dwell Time (β), a single detector measurement that approximates the travel time across a detection zone for a given vehicle. Bluetooth Dwell Time is calculated using the following equation:

$$\beta = Time\ of\ Last\ Hit - Time\ of\ First\ Hit \qquad \textbf{Equation 2}$$

Note that **Equation 2** is only valid in cases where a vehicle is detected more than once at the same Bluetooth detector. Additionally, as it is a single detector measurement, the direction of the measurement can only be determined if there is information from more than one detector. If the vehicle was detected at an upstream detector, then the direction of travel can be determined immediately. If the vehicle was not detected at an upstream detector, but was detected at a downstream detector, the direction of travel can be determined, but there is a time lag associated with the measurement, because the direction of travel cannot be determined until the vehicle travels to and is detected at the downstream detector.

Figure 3-7 shows how dwell time would be calculated for a Bluetooth enabled vehicle that is detected more than one time. The concept of True Dwell Time is illustrated to show that the Bluetooth measurement is subject to measurement error due to the Bluetooth detection process. BlueSynthesizer is capable of reporting both measurements.

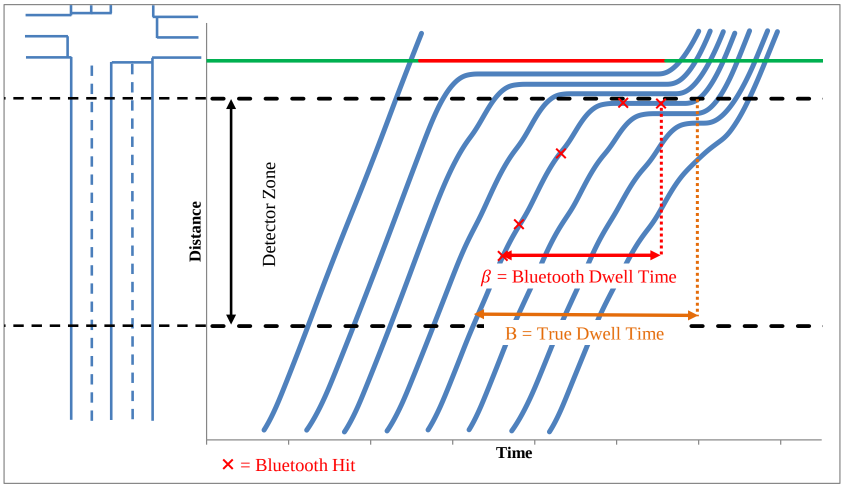

Figure 3-7: Bluetooth dwell time at a signalized intersection

Bluetooth Dwell Time was considered as a potential MOP as it was assumed that if vehicles were consistently experiencing a long travel time across a detection zone (approximately 100m in diameter) and there are no nearby traffic signals, it would be likely that a queue is present in the detection zone. It was hypothesized that if there were continually long dwell time at an upstream detector, it would indicate possible congestion due to the queue extending backwards. In addition, due to the fundamentals of traffic signal operation, it was assumed that there would be a theoretical maximum of this measurement related to the saturation flow rate when a signal is operating at capacity or above. This concept is illustrated in **Figure 3-8**, where the relationship between Bluetooth Dwell Time and volume was shown as linear in non-congested operation for illustration purposes.

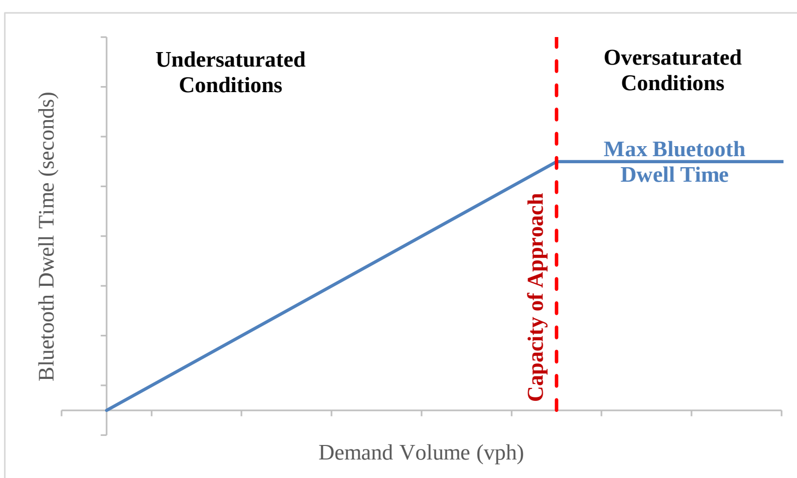

Figure 3-8: Bluetooth Dwell Time theoretical maximum

The concept of this maximum was of interest as it could be particularly valuable at detectors upstream of a traffic signal, where a prolonged period of the max Bluetooth Dwell Time could indicate whether the queue has extended to this point. It would be analogous to a system loop detector in a conventional TRPS system, however it would be capable of detecting queues over a wider area, rather than a single loop detector's point occupancy measurement.

3.3.3 Number of Hits

The final proposed MOP is the Number of Hits, the amount of times a vehicle is detected in a single detection zone. The value is different than the other measurements, as it is a discreet measurement. It was expected that Number of Hits would be correlated with Bluetooth Dwell Time as it is hypothesized that vehicles are detected more often the longer they are in the detection zone based on the fundamentals of the Bluetooth detection process. The Number of Hits per vehicle would be aggregated over a specified time period and be measured as an average of the number of Bluetooth detections per vehicle.

The rationale behind selecting Number of Hits as a MOP is that when a vehicle is detected more at single detector, the likelihood that vehicle is moving at a low rate of speed, or stationary, is higher. This can be seen as a surrogate for loop detector occupancy, as the greater the number of hits the longer a vehicle "occupies" the detection zone, similar to the Detected Dwell Time. This measurement has the disadvantage of being an abstraction of the traffic state on the network rather than a direct measurement in contrast to the other two MOPs, however it was still considered due to the similarity between it and the current functionality of loop detectors for TRPS systems.

3.4 True Measures of Performance

The base objective of a TRPS system is to reduce the delay experienced by vehicles on one or more approaches at intersections that are part of the system. To this end, it was proposed that travel time is used as the true MOP when considering the simulation experimentation. This is due to the ability of Vissim to easily output the travel time between any two points for all vehicles in the network.

When vehicles cannot change routes, and trips cannot be cancelled, then minimizing travel time is equivalent to minimizing delay. The concept of Travel Time is introduced in the below equation and illustrated in **Figure 3-9**.

$$\textit{Travel Time} = \textit{Base Travel Time} + \textit{Delay} \qquad \textbf{Equation 3}$$

Where,

Base Travel Time = Time for a vehicle to travel between any two locations on the road when travelling at a constant desired speed.

Delay = Time in excess of the Base Travel Time.

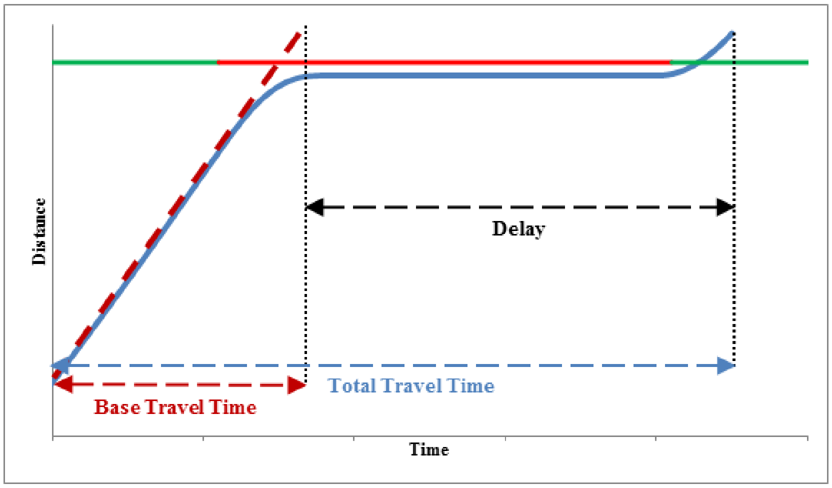

Figure 3-9: Representation of Total vs Base Travel Time

The above figure shows delay that would be associated with a traffic signal, but the delay could come from anything else that impedes travel. From an operational standpoint, having the Base Travel Time behave as a constant value gives the Total Travel Time the property that any reduction in Total Travel Time is automatically a reduction in delay.

It is important to note that the travel time could be measured for one approach or for an entire intersection, which leads to some situations where minimizing the sum of travel times from all vehicles traversing the intersection results in an increase in the travel times experienced by vehicles on one approach.

The next chapter describes in more detail Experiments 1 and 2 and presents and interprets their results.

4.0 Simulation Assessment of Bluetooth Measures of Performance

The sequential approach to the research in this thesis was defined in the previous chapter (**Figure 3-1**). This chapter describes Experiments 1 and 2 and presents and interprets their results.

4.1 Experiment 1: Identification and Assessment of Bluetooth MOPs

As presented in **Section 3.3**, there are three main MOPs that were proposed for use in Bluetooth enabled TRPS selection. However, the accuracy of these MOPs needed to be established in order to determine which MOP(s) would be best suited for use TRPS. The assessment of the MOPs in relation to the simulated true travel times is the focus of Experiment 1.

4.1.1 Experiment 1 Overview and Inputs

The simulation experiment was based on the Hespeler Road and Pinebush Street intersection with two Bluetooth detectors simulated. The detectors are assumed to have a maximum detection range of 100m. The detectors were separated by 250 metres, preventing the overlap of detection zones. Only the southbound direction of travel was simulated to reduce the computational load. The Vissim network with a visualization of where the Bluetooth detectors were located can be seen in **Figure 4-1**. Note, although the Bluetooth detectors are overlaid on the Vissim network, the BlueSynthesizer software is run separately from Vissim, and the image approximates where the detection zones would be based on the selected Bluetooth parameters.

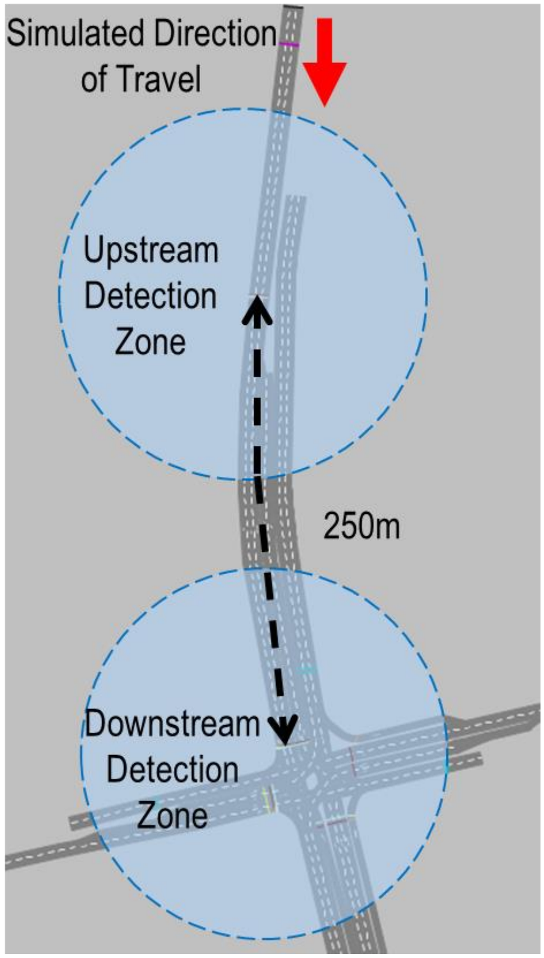

Figure 4-1: Experiment 1 network and detector layout

To establish any potential relationships between the MOPs and the true travel time the following parameters were set for the simulation experiment:

- The data were aggregated over a 5-minute period;
- The level of market penetration of Bluetooth devices was assumed to be 10% (i.e. any given vehicle within Vissim had a 10% chance of being considered to contain a Bluetooth device);
- The Bluetooth detectors were assumed to have an effective radius of 100 metres; and
- The southbound approach true travel time was measured from the location of the upstream Bluetooth detector (located approximately 250 metres upstream of the stop line) to just downstream of the intersection stop line.

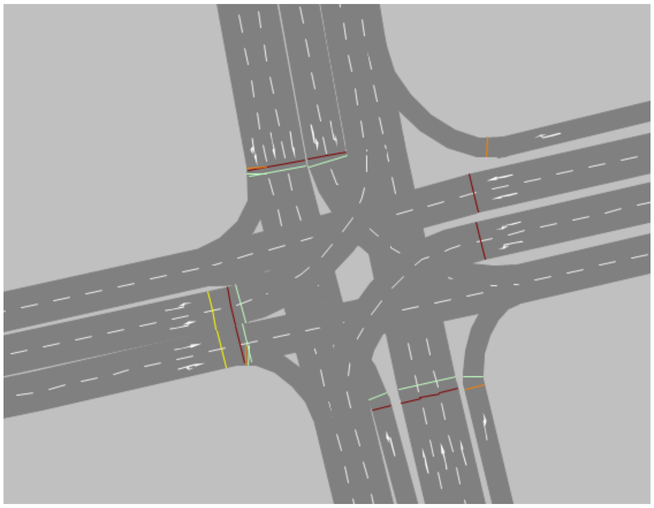

Figure 4-2: Lane configuration of simulated intersection.

The existing signal at Hespeler Road and Pinebush Street operated with an actuated 8-phase timing plan (protected left turns and protected through/right-turn phases for each approach). Consequently, the simulations were carried out using a similar 8-phase timing plan, but operating as fixed-time, the relevant parameters which can be seen in **Table 4-1**. Note that the southbound left movement was fully protected, and consequently the absence of simulated northbound traffic did not influence the southbound left capacity.

Table 4-1 – Summary of signal parameters for southbound direction

Parameter	Value	
Cycle Length	110	seconds
Amber	4	seconds
All Red	3	seconds
Southbound Left Green	11	seconds
Southbound Through-Right Green	34	seconds
Approximate Through & Right Capacity (Synchro)	1450	vph
Approximate Through & Right Capacity (Vissim)	1652	vph
Approximate Left Capacity (Synchro)	306	vph
Approximate Left Capacity (Vissim)	394	vph

The above table presents the approximate capacities that were calculated by Synchro Studios (a macroscopic simulation tool primarily used for signal timing development) and measured on a per-lane group basis in Vissim. The capacity represents the amount of vehicles that are expected to be able to proceed through an intersection over an hour. Synchro uses the Highway Capacity Manual (2010) methodology to calculate the capacity of intersection movements based on signal timings and vehicle demands. However, in Vissim there is no similar calculation, as the behaviour of the vehicles dictates the capacity of a movement. Instead, the capacity was approximated by overloading the vehicle demand for the signal timing plan and measuring the number of vehicles that proceeded through the intersection in an hour.

As the capacity of a movement represents the theoretical maximum amount of vehicles that can be served before an intersection operates in oversaturated conditions, the ratio of demand volume to the capacity (v/c ratio) is used to express how close the intersection is operating to capacity. The estimates of capacity from the two software packages results allowed for the determination of demand volumes that could be reasonably expected to produce over or undersaturated conditions.

Using the capacity estimates above, a range of hourly volume demands were selected to create both under and oversaturated conditions. The demand volume was gradually increased each simulated hour to allow for a range of traffic conditions to be observed. The previously defined signal parameters were used with 12 hours of traffic demands simulated in Vissim. Each hour represented a different demand case, with undersaturated conditions simulated first. In addition to the increase of the demand volume, 900 seconds (15 minutes) of warm-up time using the base first volume demand was simulated. The concept of a warm-up or seeding period is common to microsimulation analysis as it allows vehicles to progress through the network at a time when measurements are not recorded. This allows the measurements recorded by the software to not be influenced by vehicles that have better than expected travel times due to the fact that they are not impeded by other vehicles.

Table 4-2 summarizes the hourly volumes that were used in the simulation model. Based on the volume inputs and the estimated capacity, it was expected that before simulation hour 5, the signal would be operating in undersaturated conditions, and between hours 5 and 10 the intersection would be operating in oversaturated conditions. The turning percentages were held constant at 20% turning right, 60% proceeding through, and 20% turning left.

Table 4-2: Summary of Vissim volume inputs.

Simulation Hour	Southbound Approach Demand (vph)	Through & Right Turn Demand (vph)	Left Turn Demand (vph)	Estimated v/c	
				Through & Right Turn	Left Turn
1	1600	1280	320	0.77	0.81
2	1800	1440	360	0.87	0.91
3	1900	1520	380	0.92	0.96
4	2000	1600	400	0.97	1.02
5	2100	1680	420	1.02	1.07
6	2200	1760	440	1.07	1.12
7	2300	1840	460	1.11	1.17
8	2400	1920	480	1.16	1.22
9	2400	1920	480	1.16	1.22
10	2300	1840	460	1.11	1.17
11	1600	1280	320	0.77	0.81
12	1600	1280	320	0.77	0.81

With the simulation complete, the travel times recorded by Vissim and the vehicle trajectory file processed by BlueSynthesizer, the data to assess the proposed MOPs was completed.

The MOPs presented in the previous chapter were conceptually defined for a single vehicle, and in order to be used as a MOP they must be calculated as an aggregated value. The below equations present how each of the MOPs are aggregated for an interval, k. Due to the nature of simulation both the true travel times and Bluetooth travel times are known for the entire simulation period, however to assess the data as if it was collected in real-time the data were aggregated without information from the next time period. For example, if the interval was 5 minutes long, and a vehicle is detected at the upstream detector at time 4:30 for interval k, and then is not detected until time 0:30 of the next interval (k + 1), this vehicle's travel time would **not** be included in the interval k, but rather would be included in interval k + 1. However, if the vehicle was detected multiple times at the downstream detector and at least one detection occurred prior to the end of interval k and at least one occurred after the start of interval k + 1, then there would be a travel time for both interval k and k + 1 associated with the vehicle. This principle applies for all of the MOPs, insofar that the per-vehicle measurements may start and end in different intervals, depending on the time of their last detection.

The aggregate Bluetooth Travel Time is defined by the following equation:

$$\overline{TT}_B^k = \frac{\sum_{i=1}^{n} TT_{Bi}^k}{n}, \forall\ i\ in\ interval\ k \qquad \textbf{Equation 4}$$

Where,

$\overline{TT}_B^k$ is the average Bluetooth Travel Time for all vehicles in interval *k*.

TT_{Bi}^k is the Bluetooth Travel Time for vehicle *i* in interval *k* (as defined in **Equation 1**). This value was calculated for first-first, first-last, and average-last travel times.

n is the number of reported Bluetooth Travel Times in interval *k*.

The average Bluetooth Dwell Time is defined by the following equation:

$$\bar{\beta}^k = \frac{\sum_{i=1}^{n} \beta_i^k}{n}, \forall\ i\ in\ interval\ k \qquad \textbf{Equation 5}$$

Where,

$\bar{\beta}^k$ is the average Detector Dwell Time for all vehicles in interval *k*.

β_i^k is the Detector Dwell Time for vehicle *i* in interval *k* (as defined in **Equation 2**). Note that only vehicles with at least 2 hits in interval *k* will have a detector dwell time associated with them

n is the number of reported Bluetooth Dwell times in interval *k*.

The average Bluetooth Number of Hits is defined by the following equation:

$$\overline{NH}_B^k = \frac{\sum_{i=1}^{n} NH_i^k}{n}, \forall\ i\ in\ interval\ k \qquad \textbf{Equation 6}$$

Where,

$\overline{NH}_B^k$ is the average Number of Hits per vehicle for all vehicles in interval *k*.

NH_i^k is the Number of Hits for vehicle *i* in interval *k*.

n is the number of vehicles with hits recorded in interval *k*.

Figure 4-3 illustrates this aggregation for computing the average Bluetooth Dwell time. In this example there are two Bluetooth enabled vehicles which have recorded Bluetooth Dwell time measurements. For this sample interval, *k*, average Bluetooth Dwell time would be equal to the average of β_1 and β_2 as both times of last detection occur within the same interval. If the final hit associated with β_1 occurred in interval *k* + 1, the next latest hit in interval *k* would be used to calculate β_1. Note that this figure is for illustrative purposes only, and the intervals used in the experiment are longer in duration than illustrated, as the 5-minute interval selected would allow for almost three traffic signal timing cycles to complete before ending. The decision was made to have the interval to be longer than the cycle length to ensure that there was no bias in the measurements as a result of the reporting interval occurring at the same time and duration as a green or red phase for the direction of interest.

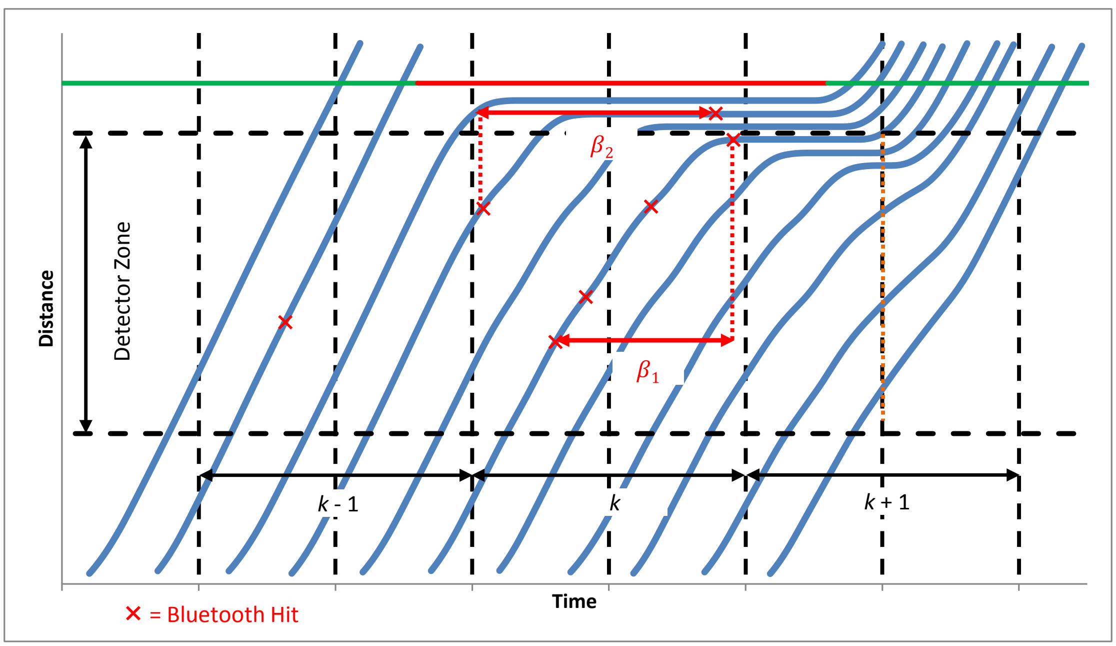

Figure 4-3 – Time-space diagram of vehicles progressing through detection zone.

The motivation for this experiment was to assess the errors that are inherent in Bluetooth detector measurements, in particular:

1. Sampling error which arises from:

   a. The Level of Market Penetration (LMP) of Bluetooth,
   b. The volume of traffic on the network, and
   c. The data collection interval.
2. Limitations of Bluetooth Detector range as the area measured is often only a portion of the intersection's approach.

These errors associated with Bluetooth measurements were assumed to result in a difference between the true travel time and the Bluetooth Travel Time. The overall accuracy of the measurements is the primary interest in this experiment, with less of a focus on the extent to which each source of error contributes to the difference in travel times. With the inputs specified above the experiment was completed and the results are presented in the following section.

4.1.2 Experiment 1 Results

The simulated Vissim and BlueSynthesizer data were processed and summarized for comparison of the MOPs and regression-based analysis. The true travel time and dwell time were produced from data supplied by the Vissim simulation, and the corresponding Bluetooth MOPs were produced from the BlueSynthesizer software. With the aggregation interval specified at 5 minutes, the 12 hours of simulation time resulted in 144 intervals to be used to assess the relationship between the Bluetooth and True MOEs.

4.1.2.1 Average Travel Time:

The first comparison that was completed focused on which Bluetooth Travel Time calculation methodology would be the most beneficial for the application of Bluetooth detectors in TRPS. To assess the appropriateness of each of the travel time measurements, the 12 hours of data that were aggregated in 5-minute intervals were plotted with the True Travel time. The Bluetooth Travel Time methodologies that were considered were:

- First-first (the difference in time between the first detection of a vehicle at the upstream detector and the time of the first detection at downstream detector);
- First-last (the difference in time between the first detection of a vehicle at the upstream detector and the time of the last detection downstream detector); and
- Average-last (the difference in time between the average time of detection of a vehicle at the upstream detector and the time of the last detection downstream detector).

Figure 4-4 shows the aggregated 5-minute true travel time and the above Bluetooth Travel Times as a function of simulation time. This plot serves two purposes: (1) to determine which methodology tracks the True Travel Time the closest, and (2) to confirm that the chosen inputs result in periods of undersaturation and oversaturation.

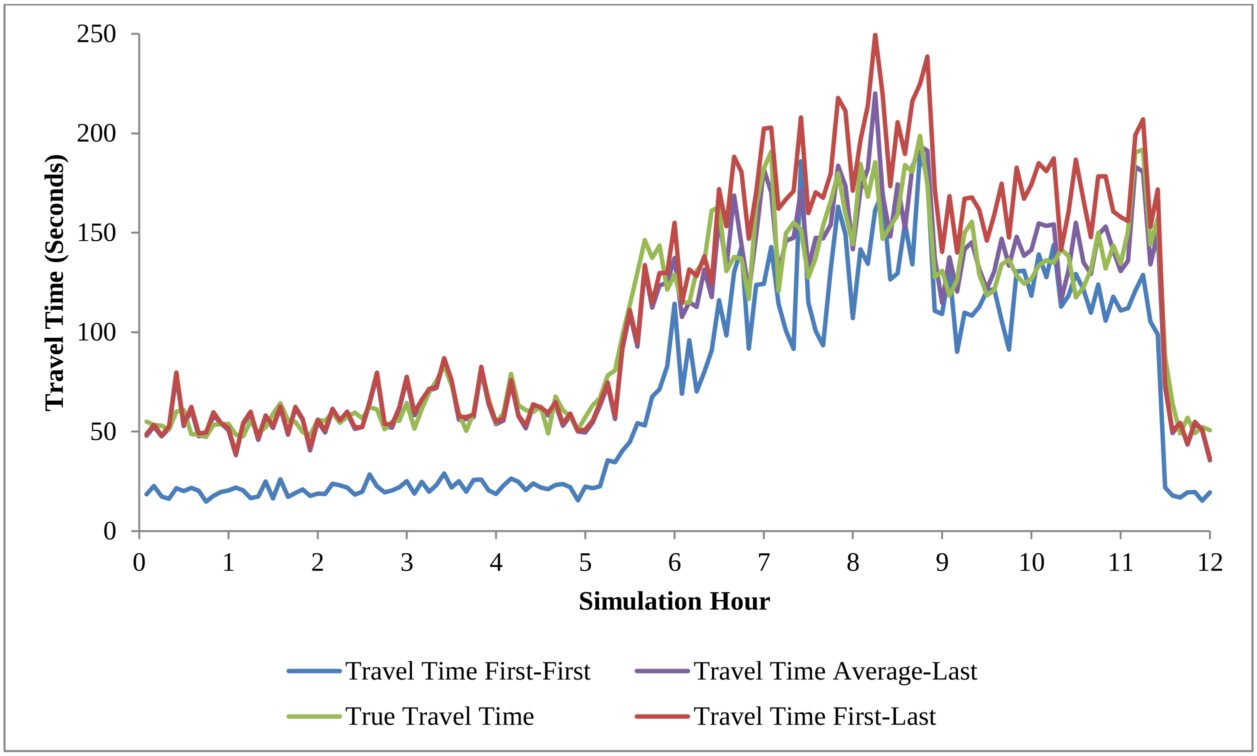

Figure 4-4 – Comparison of Travel Time measurements for study approach.

The above figure shows that for approximately the first 5 hours of the simulation, the approach is undersaturated and approach travel times average approximately 60 seconds. As a point of context, the average vehicle delay for the approach was estimated to be 46 seconds using the methodology in the Canadian Capacity Guide for Signalized Intersections (2008) and the existing signal timing plan and base volumes. For most of the remaining 7 hours of the simulation, the approach is oversaturated and travel times are much longer. This confirms that the proposed volume inputs were correctly selected to vary the conditions on the approach as intended based on the capacity estimates.

It can also be observed that, as expected, Bluetooth Travel Times using the first-first methodology tend to under predict the true travel time and both the first-last and the average-last methodologies are closer to the True Travel Time.

In addition to the comparison of the travel times completed above, each of the Bluetooth Travel Times were assessed using linear regression to the True Travel Times for the approach. The regressions carried out are as follows:

$y = Ax_j + b$

Where:

y = average True Travel Time (seconds)

A, B = linear regression parameters

x_j = average Bluetooth measured travel time

- j = 1: First-First Travel Time (**Figure 4-5**);
- j = 2: First-Last Travel Time (**Figure 4-6**); and
- j = 3: Average-Last Travel Time (**Figure 4-7).**

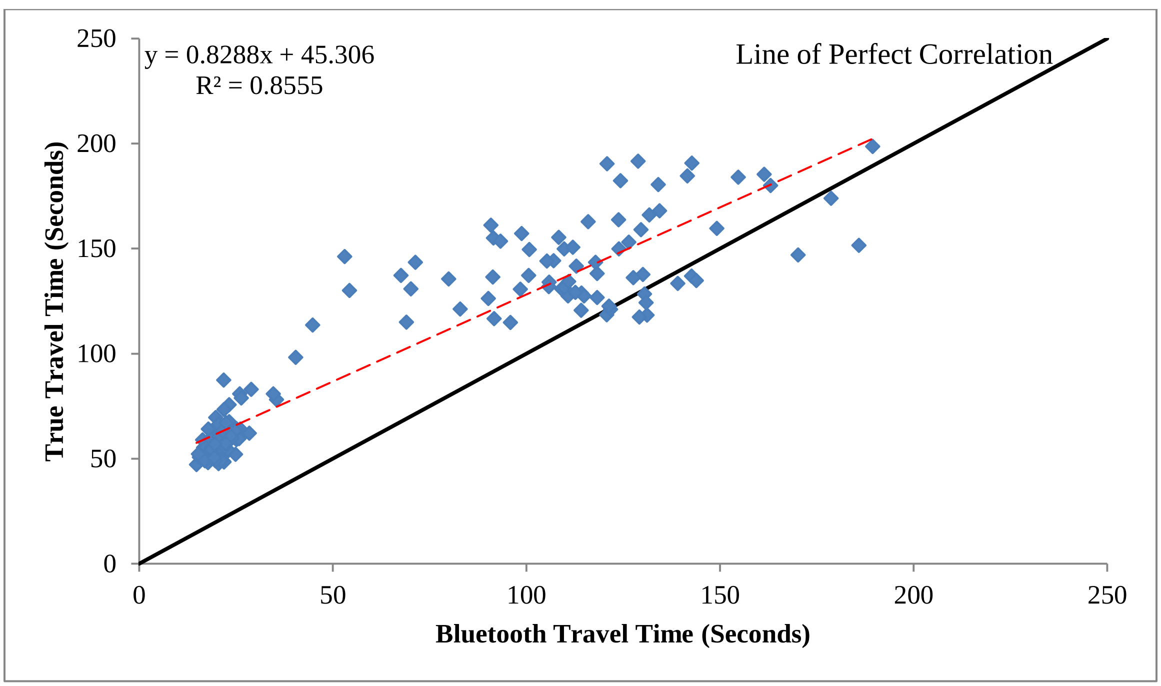

Figure 4-5 – True travel time vs. Bluetooth First-First travel time for study approach.

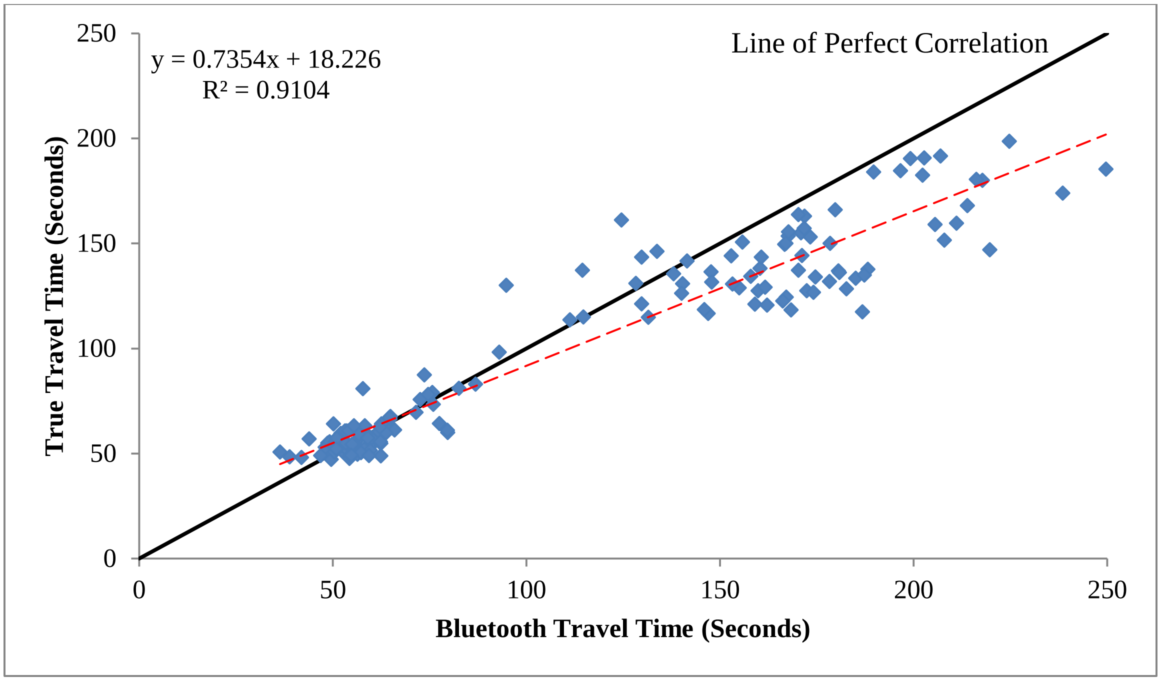

Figure 4-6 – True travel time vs. Bluetooth First-Last travel time for study approach.

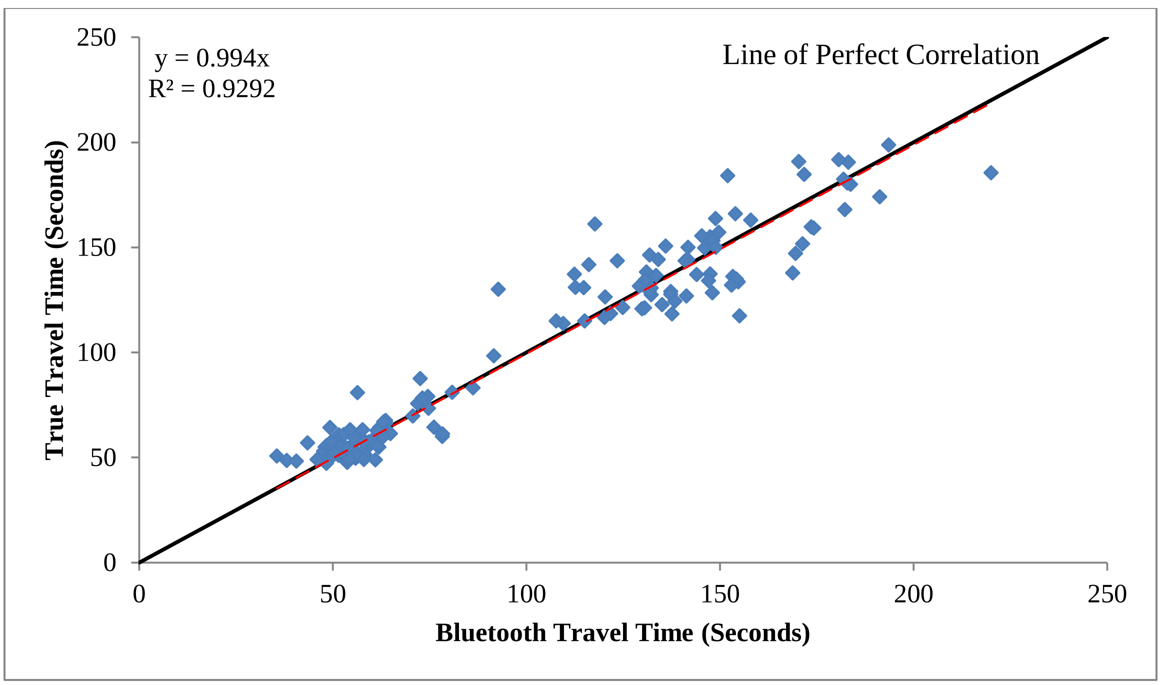

Figure 4-7 – True travel time vs. Bluetooth Average-Last travel time for study approach.

The above three plots demonstrate that the Bluetooth Travel Time, regardless of calculation method, appears to be highly correlated with the True Travel Times. From order of best to worse fit (according to R^2 value) it is average-last (0.93), first-last (0.91), and first-first (0.86). As expected from the previous plot, it is apparent that first-first results in a significant underestimation of the travel time, as the intercept value is a negative adjustment, with a slope close to one. It can also be seen in **Figure 4-5** that as the True Travel Time increases the spread of the Bluetooth Travel Time also increases, and this was hypothesized to be associated with the omission of the delay experienced at the signalized intersection.

Furthermore, **Figure 4-7** shows the relationship between the average-last travel time and the True Travel Time for the approach. The linear regression was performed and the intercept value was found to not be statistically significant and therefore set to zero. The resulting linear regression (dashed red line in figure) has a slope which is very close to 1.0 suggesting that the Bluetooth estimated travel times provide an accurate and unbiased estimate of the true travel times even when the level of market penetration is 10% and a relatively short aggregation time period of 5 minutes is used.

From these results it was concluded that Bluetooth Travel Time has a strong relationship with the True Travel Time, and that the average-last methodology of calculating the travel time is the best estimator for the field conditions in both undersaturated and oversaturated operation. The first-last methodology would also be acceptable to use in the case that the capability to calculate average-last is not possible due to vendor limitations in the field.

It should be noted that these conclusions are applicable only when the detectors are placed at the midblock (upstream detector) and at the stop line (downstream detector). If the upstream detector is located at a signalized intersection, then it is suspected that last-last methodology would be preferred (as this would avoid capturing signal delay at the upstream intersection and erroneously incorporating this as part of the travel time on the downstream approach).

Furthermore, these results assume no outliers are contained in the Bluetooth measurements. The presence of outliers in the data would increase errors and reduce the coefficient of determination (R^2). However, it is expected that these errors would impact all three ways of computing the Bluetooth travel time in the same way, and therefore would not change the selection of the best method for computing the Bluetooth travel time.

4.1.2.2 Average Bluetooth Dwell Time

The next MOP that was assessed was the Bluetooth Dwell Time, with the dwell time associated with the intersection detector summarized for this experiment. The intersection detector was selected over the upstream detector as it captures the cyclic nature of queuing at the intersection that would not be observable at the upstream detector. **Figure 4-8** shows the relationship between the average Bluetooth Dwell Time and the average True Dwell Time.

A linear regression was calibrated to the data and the intercept was not statistically significant. The R^2 value of 0.81 indicates that the linear model explains a large portion of the variability in the observed data. However, the slope is much greater than 1.0 indicating that the Bluetooth dwell times tend to under-estimate the true travel time. This under-estimation occurs because the Bluetooth dwell time is computed as the difference between the first and the last hits. Due to the nature of the Bluetooth communication protocol, these hits do not always occur immediately when the vehicle enters the detection zone or when the vehicle exists the detection zone. As such, the Bluetooth dwell time always underestimates the true dwell time.

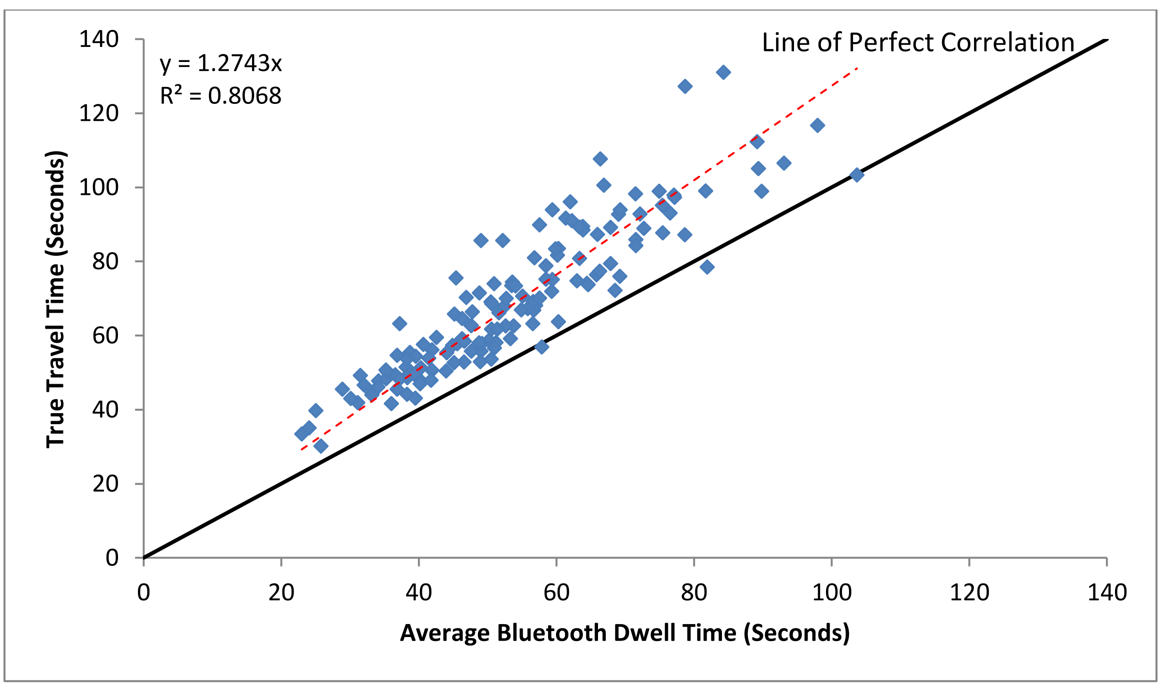

Figure 4-8 – True dwell time vs. Bluetooth dwell time for measurements at the intersection

The dwell time measurements were also compared to the true travel time, **Figure 4-9**. When compared to the other plots the overall relationship is quite weak, with an almost vertical relationship between the Bluetooth dwell time and the True Travel Time. This is expected, as the dwell time measurements can only capture the time that the vehicle spends within the detection zone of the downstream detector which extends approximately 100m upstream of the stop line. When the approach becomes oversaturated, and the queue extends more than 100m upstream of the stop line, the delay that is experienced by the vehicle in the queue upstream of the Bluetooth detection zone cannot be captured in the Bluetooth dwell time measurement. Consequently, the dwell time under-estimates the true travel time and this under-estimation becomes large when queues and delays on the approach are large.

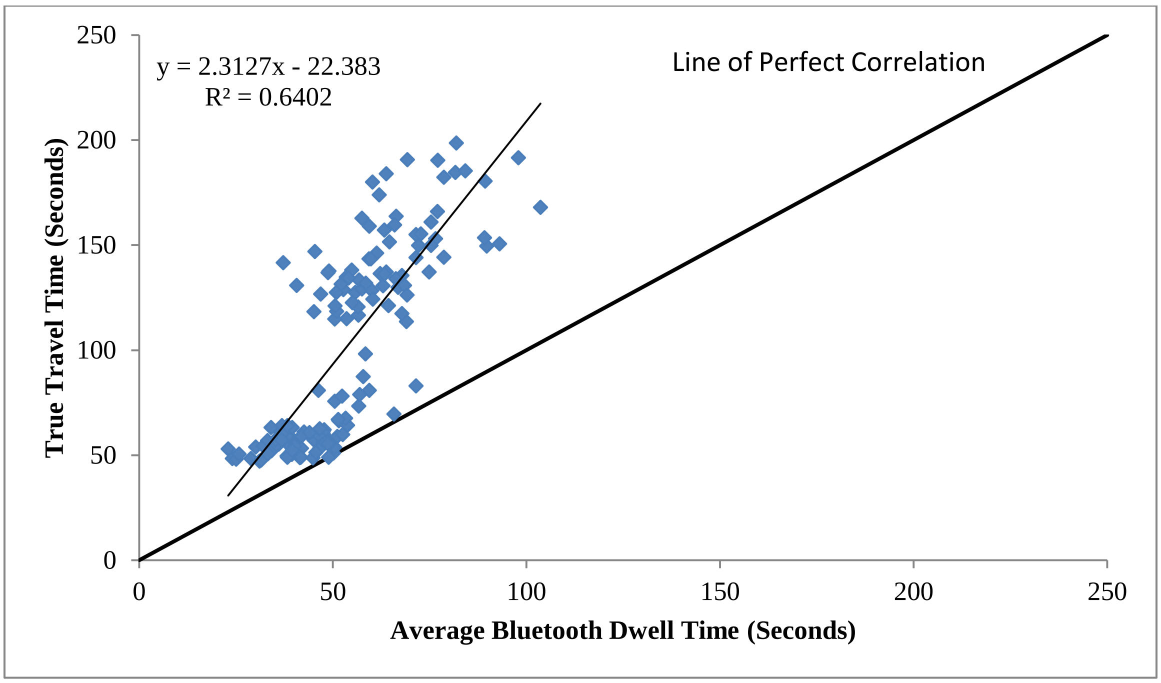

Figure 4-9 – True travel time vs. Bluetooth dwell time

4.1.2.3 Average Number of Hits

Finally, the average Number of Hits at the intersection detector were compared to the average True Travel Time (**Figure 4-10)**. From this figure, it is clear that the relationship is weak, which is primarily due to the nature of the Bluetooth detection protocol, where it is very common to have a vehicle moving at a higher rate of speed to only be detected once, which explains the clustering at lower travel times. In addition, the number of hits for a stopped vehicle would be difficult to differentiate between normal signalized delay and delay caused by oversaturated conditions, as there is no time context associated with the Number of Hits. This result makes Number of Hits an undesirable MOP for a similar reason that this research seeks to replace or supplement loop detectors, there is no direct relationship between the travel time and the parameter.

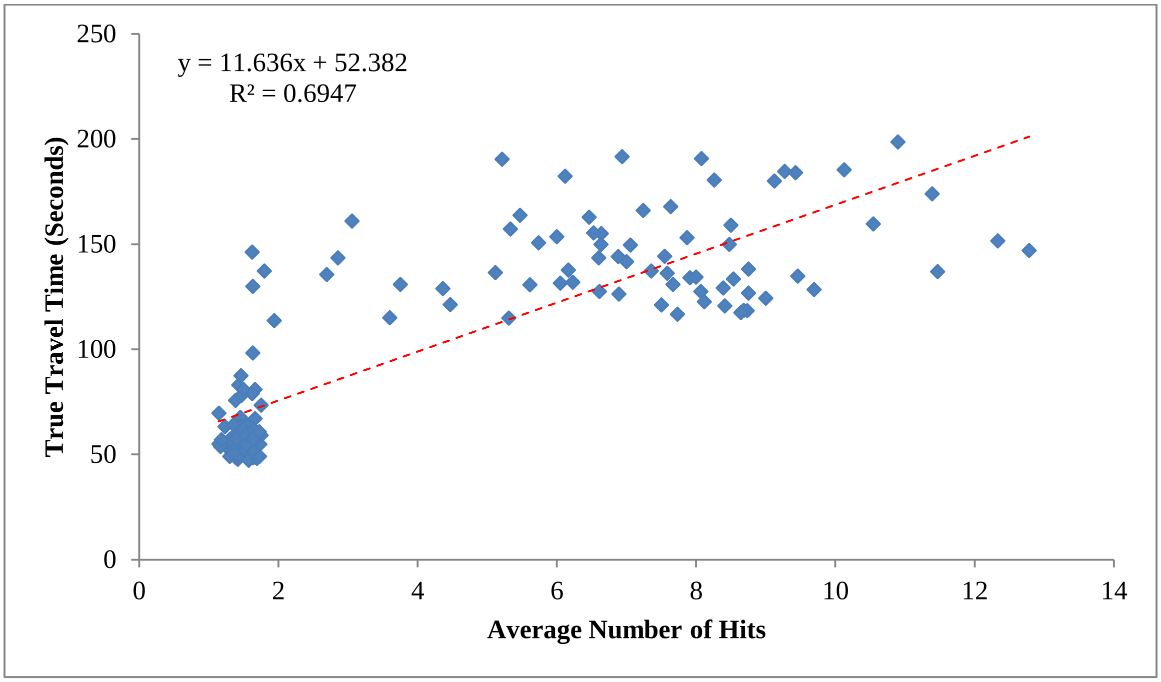

Figure 4-10 – True travel time vs. Average Number of Hits per vehicle

4.1.3 Experiment 2 Conclusions

From these results, we can make the following observations:

1. This experiment shows that, at least in simulated conditions without outliers, the average Bluetooth travel times (aggregated over 5 minute interval) can accurately reflect the average true travel times when the travel times are computed in an appropriate manner (i.e. in this case as average-last, or first-last if restricted by the in-field detector, as not all vendors allow for the calculation of average-last travel times).
2. Average Bluetooth Dwell Times are highly correlated with the average True Dwell Times, but they consistently underestimate the average True Dwell Times (by an average of 30%).
3. The average Bluetooth Dwell Times and average Number of Hits are not reliable estimates of the average true travel time when queues on the approach extend upstream of the detection zone.

The next experiment built on these results by selecting the MOP of Bluetooth Travel Time to determine the traffic state at an intersection using Bluetooth detectors.

4.2 Experiment 2: Ability of Bluetooth Travel Time to assess traffic conditions

Based on the results of Experiment 1, the average Bluetooth Travel Time MOP was selected as the MOP with the most potential to determine if adverse traffic conditions could be recognized with Bluetooth detectors. The second simulation experiment was designed to assess the ability of this MOP to identify congestion.

The experiment consisted of recording the travel times on a single intersection approach using both Vissim's simulation tools and BlueSynthesizer while varying the traffic demand and signal timing plan to determine if the 5-minute average Bluetooth Travel Time is able to identify when congestion occurs.

4.2.1 Experiment 2 Overview and Inputs

The experiment focused on the potential for the Bluetooth Travel Time to identify changes to traffic states at an intersection. To accomplish this, two traffic demand scenarios were created, the Base Demand, and the Diversion Demand (**Table 4-3**).

The Diversion Demand represents a significant increase to the southbound left turn volume and was motivated by the Hespeler Road corridor. It was assumed that an incident on Highway 401 could result in the expected traffic pattern at the intersection of Hespeler Road and Pinebush Street to shift to respond to the diversion of traffic from the highway. People experiencing congestion in the eastbound direction of travel on Highway 401 would leave the highway at Hespeler Road and then continue on Pinebush Street in the eastbound direction to attempt to by-pass the delay, resulting in a significant increase to the southbound left turn traffic. The volume increase of the southbound left was increased to the point that significant oversaturation would occur for the movement, which was estimated in Synchro, similar to the approach taken in Experiment 1.

Synchro was used to develop two fixed time signal timing plans that were optimized for each of the two traffic demands, and these timings were used as an input into the Vissim model. For simplicity the traffic demands and traffic signal timing plans are referred to as follows:

- Base Demand: Traffic demand based on the existing turning movement counts;
- Diversion Demand: based on the Synchro estimate of an overcapacity movement, that can still be served by a reasonable cycle length
- Base Signal Timing Plan: Created in Synchro by optimizing the signal timing plan for the Base Demand; and
- Diversion Signal Timing Plan: Created in Synchro by optimizing the signal timing plan for the Diversion Demand.

Table 4-3 – Summary of southbound volumes by movement for test scenarios

Scenario	Movement	Traffic Volume (vph)
Base Demand	Southbound Left	300
	Southbound Through	980
	Southbound Right	304
Diversion Demand	Southbound Left	600
	Southbound Through	980
	Southbound Right	304

The traffic demands were held constant for each simulation scenario, and each scenario was run for 4 hours, resulting in 48 observations at 5-minute aggregation.

4.2.2 Experiment 2 Results

For each of the four simulation scenarios the average True Travel Times and the average Bluetooth Travel Times were computed using the Vissim and BlueSynthesizer outputs. The mean and standard deviation of travel times for these four scenarios were calculated to assess whether or not there was a difference in the travel times for the two volume cases for each signal timing plan. **Table 4-4** shows the results for the truth and Bluetooth travel times (average-last) respectively.

Table 4-4 – True and Bluetooth travel times for southbound approach

Signal Plan	Summary Statistic	Travel Times (seconds)			
		Base Demand		Diversion Demand	
		True	Bluetooth	True	Bluetooth
Base Signal Plan	Mean	51.8	51.3	196.9	178.7
	Standard Deviation	4.3	9.4	24.9	56.4
SBL Signal Plan	Mean	49.5	51.4	52.1	53.5
	Standard Deviation	4.1	9.6	4.0	7.7

The mean and standard deviation were then used to create normal distributions (the mean ± 3 standard deviations) of the travel time as a way of visually representing the difference in the average travel time measurements between the two traffic demand scenarios for a given signal timing plan (**Figure 4-11).**

From the figure it is easy to observe that there is a discernible difference between the true travel time distributions associated with the two traffic demand scenarios. There is also a discernable difference between the Bluetooth measured travel time distributions, however, the Bluetooth travel times exhibit a larger variance and consequently there is some overlap between these two distributions. The difference in the width of the two distributions for both the true and Bluetooth travel time is due to the diversion scenario and the fact that no particular subset of vehicles was assigned to either movement. Vehicles that turn left experience significantly higher delay than those that travel straight through the intersection. This results in a wider distribution of the travel times, as once southbound vehicles pass the queueing associated with the overcapacity left turn, they have a significantly lower travel time.

Thus, if in a 5-minute interval the average Bluetooth travel time was measured to be 110 seconds, and the current operating conditions were the Base signal timing plan, then it could be safely concluded that the traffic demands are substantially different from the base traffic demands and a different traffic signal timing plan should be selected.

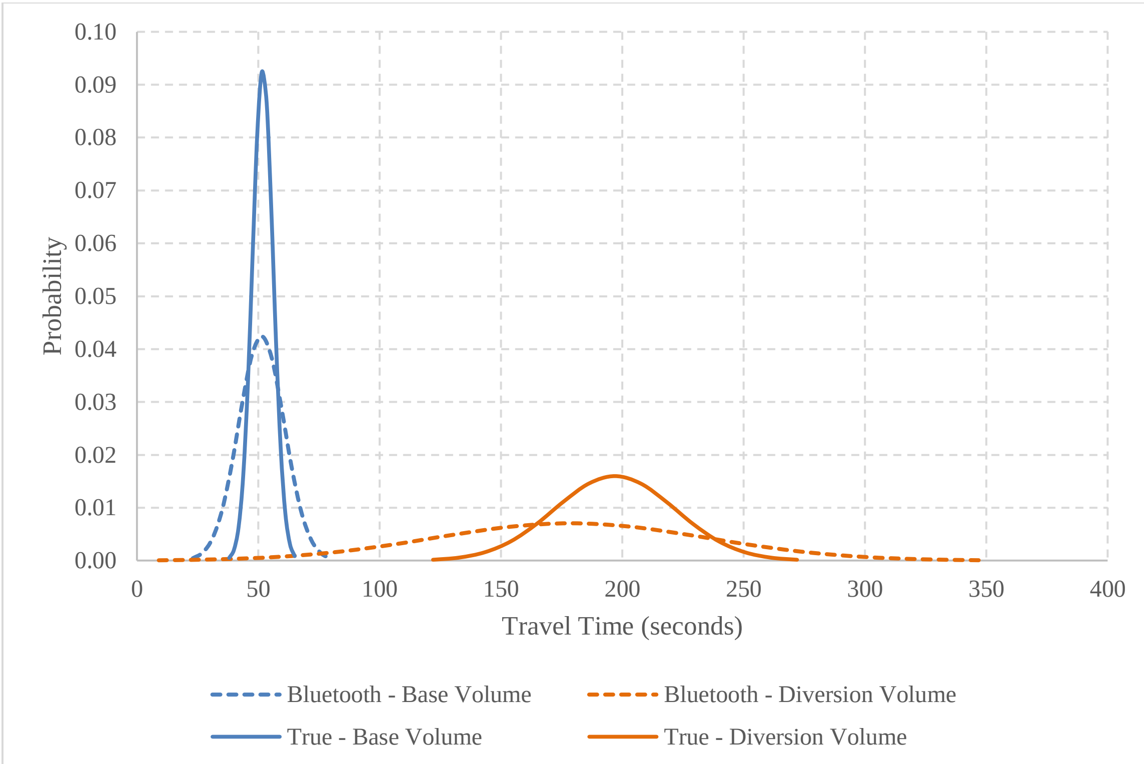

Figure 4-11 – Distribution of True travel times for base signal timing plan

4.2.3 Experiment 2 Conclusions

The goal of this experiment was to determine the potential for identifying a change in traffic state on the basis of average Bluetooth travel times as a pre-requisite step to using Bluetooth detector measurements as a means for selecting traffic signal timing plans in a Traffic Responsive Plan Selection system.

It was found that:

1. The mean of the distribution of the 5-minute average Bluetooth travel times corresponded closely to the mean of the distribution of average true travel times; however, the standard deviation of the Bluetooth data is consistently larger than the standard deviation of the true travel times (on average, across the four cases, the Bluetooth standard deviations are 2.2 times larger than the standard deviation from the true travel times). This finding is not surprising, given the stochastic nature of the Bluetooth detection process.
2. The additional variability in the Bluetooth travel times makes it more challenging to be able to discern when the underlying traffic states have changes. However, the example investigated shows that when these states are sufficiently different (as would likely be the

case when traffic diverts from a heavily travelled freeway onto the surrounding arterial network as a result of an incident on the freeway) Bluetooth measurements (i.e. 5-minute average Bluetooth travel times) can be used to discriminate between these states.

With the simulation experiments demonstrating potential to (1) accurately measure the vehicle travel time, and (2) determine when the network is operating in sub-optimal conditions. It was decided that a field pilot study would be conducted to assess the potential of the system in the field, with the study and its findings presented in the next chapter.

5.0 Bluetooth Pilot Study and Preliminary Results

The two simulation experiments described in the previous Chapters illustrated that there was potential for Bluetooth detectors to be used to measure traffic conditions in the field. These results of the preliminary simulations informed the development of a field pilot study in Cambridge, Ontario. In partnership with the Region of Waterloo, Transport Canada, and CIMA+ two sections of the Hespeler Road corridor were equipped with Bluetooth and Wi-Fi detectors. A corresponding segment of Highway 401 which had Bluetooth detectors installed as part of a different project were used to monitor the conditions on the highway to determine when or if any delays were experienced by vehicles traveling on the highway.

This thesis focuses on the result of the Bluetooth detectors located in the first study section, however the full pilot study is presented in this section as the design of both pilot study areas was part of the work completed in support of the thesis.

This study only gathered data for post-processing to assess which measurements could be used for TRPS; there were no interactions between the Bluetooth detectors and traffic signal controllers in this pilot study.

5.1 Pilot Study Instrumentation Plan

In collaboration with the Regional Municipality of Waterloo, Transport Canada, and CIMA+, a field pilot study was conducted at two locations on Hespeler Road in Cambridge, Ontario. Location 1 is the intersection of Hespeler Road and Pinebush Street, located at the north end of the corridor just south of Highway 401. The second location is the intersection of Hespeler Road and Bishop Street North, which is approximately the halfway point of the study corridor. The pilot study involves both Bluetooth detectors and Wi-Fi detectors from multiple vendors to maximize the areas that can be instrumented. Wi-Fi detectors operate under the same concept as Bluetooth detectors, and were included in the pilot study to support other areas of research.

5.1.1 Pilot Area 1: Hespeler Road at Pinebush Street

This pilot area was selected as the primary location of interest for these research due to the high baseline traffic demand on the intersection and proximity to Highway 401. It had been the Region’s experience that it was particularly susceptible to congestion from variation of traffic demand, as it is already a heavily utilized intersection.

The pilot area was equipped with the following types of instrumentation:

- Bluetooth detectors;
- Intersection-based Wi-Fi detectors;
- Traffic pucks (point source loop detectors); and
- Video cameras.

The location of these sensors was informed by the Bluetooth simulations. The corridor was already equipped with traffic sensor pucks that provide the volume and occupancy for incoming approaches, and additional detectors were installed in the proximity of the upstream detectors. Video cameras were mounted on utility or signal poles to be used as a way to validate if the intersections are experiencing congestion. **Table 5-1** is the legend for the pilot study equipment that is illustrated in **Figure 5-1**.

Table 5-1 – Legend for detection instrumentation

Symbol	Instrument
●	Traffic Sensor Puck Station
◀	Video Camera
D	Bluetooth Detector
W	Wi-Fi Detector

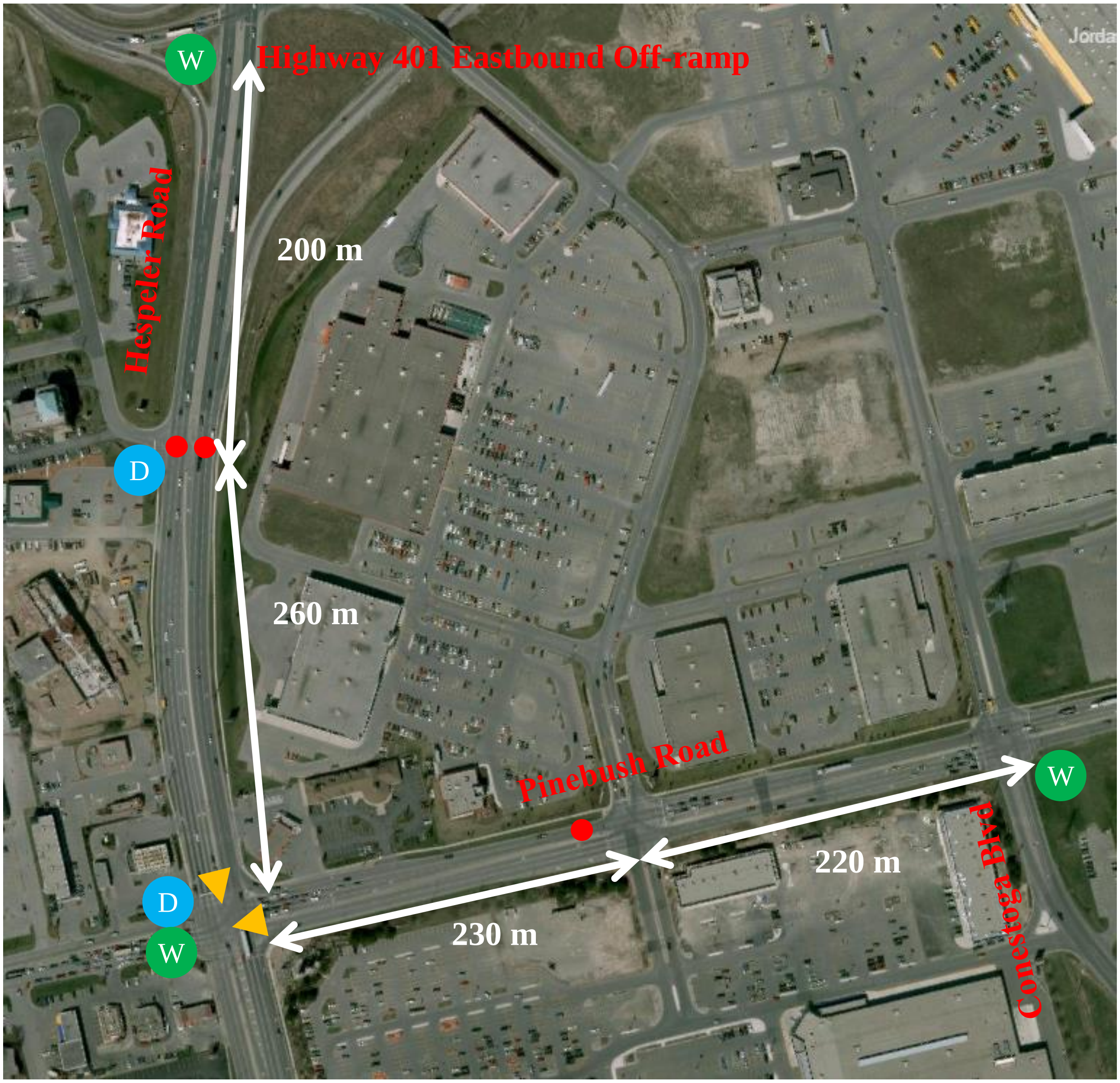

Figure 5-1 – Overview of first pilot intersection (Image from Google Maps)

The motivation for this detector layout was unique to each pair of detectors. The one of greatest interest was the midblock Bluetooth detector paired with the Bluetooth detector at the intersection of Hespeler Road and Pinebush. This configuration closely matched the simulation experiments, as the upstream detector would not include signalized delay. The pair of Wi-Fi detectors located at the Highway 401 off-ramp and Hespeler Road, and Hespeler Road and Pinebush Road provide a data set that would include the delay of two signalized intersections, which is an extension of the simulation scenarios. The final detector pair is along Pinebush Road between Hespeler Road and Conestoga Boulevard, as these Wi-Fi detectors are both located at signalized intersections, and there is an intermediate signalized intersection that would contribute to the measured delay.

5.1.2 Pilot Area 2: Hespeler Road from Sheldon Drive to Dunbar Road

Although not the focus of this research, a second pilot area was instrumented, with **Table 5-1** containing the legend for the pilot study equipment that is illustrated **Figure 5-2**, which depicts the equipment layout for the pilot location.

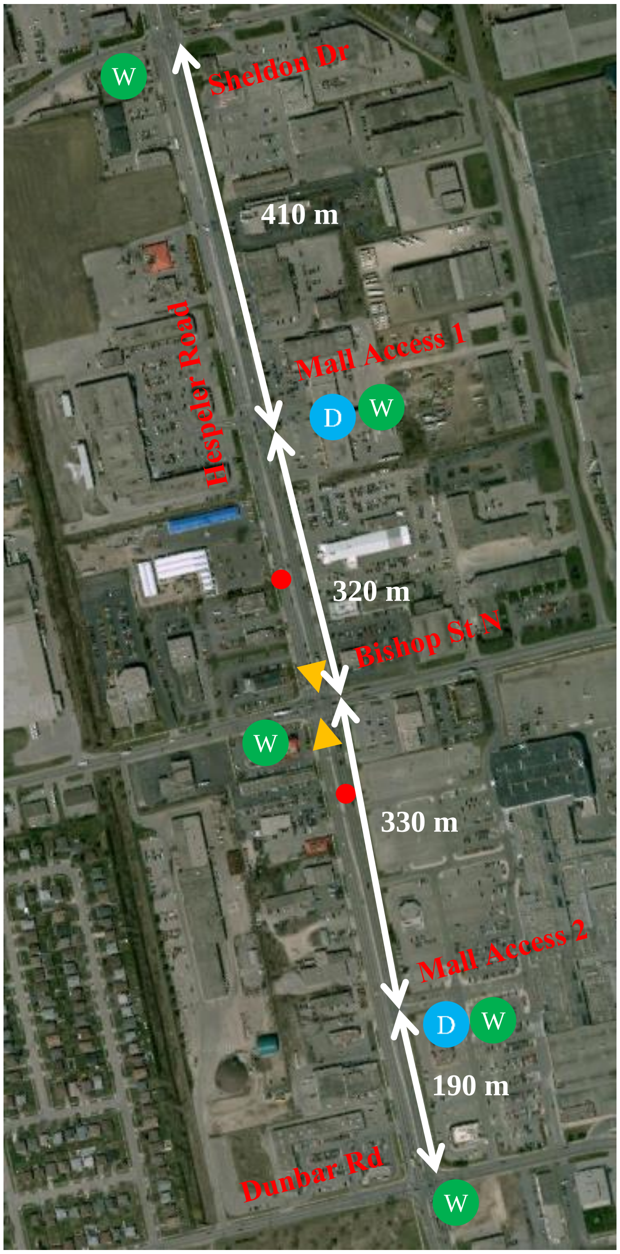

Figure 5-2 – Overview of the second pilot intersection (Image from Google Maps)

Similar to Pilot Area 1, the detector pairs were selected to determine the impact of intermediate intersections on Bluetooth travel times, which was not the primary focus of this research.

5.1.3 Highway 401 Detector Location

Through the development of the pilot study, there was information provided on another pair of Bluetooth detectors that were deployed as part of travel time monitoring on Highway 401. Although separate from the design of the pilot study, the data were provided to the research team for review of the traffic conditions on Highway 401 for the duration of the Hespeler Road study. The Bluetooth detectors were located at the interchange of Highway 401 with Homer Watson Boulevard and Highway 401 at Townline Road, their approximate locations can be seen in **Figure 5-3**. The location of the detectors were ideal for use in this pilot study, as the travel time of the segment that was recorded crossed the study area, and any congestion between these two points would likely have been captured by the detectors.

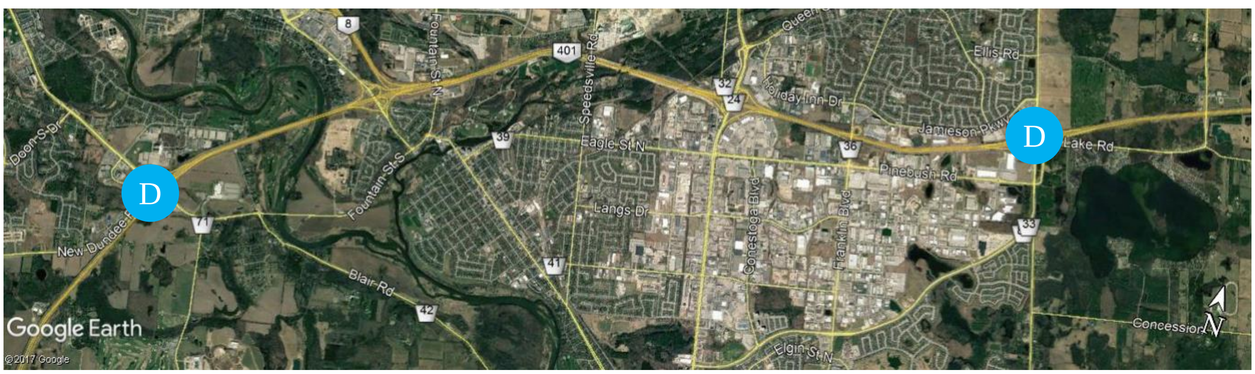

Figure 5-3 – Highway 401 detector locations

5.2 Pilot Study Objectives

The objective of the pilot study design was to obtain data that would be useful to this thesis and future research efforts. The two pilot areas allowed for a variety of detector pairings to assess the impact that the relative location of the detectors have on the measurements for both the two detector measurements (typically travel time) and the one detector measurements (dwell time).

In addition to the various pairings, the objective for this research was to examine the ability of Bluetooth detectors to identify atypical conditions, similar to the process in the simulation experiments. This assessment provided the o opportunity to derive an algorithm that would use Bluetooth travel time to determine a change in traffic conditions. The derivation of the algorithm was produced in a separate research document as part of the project in partnership with the Region of Waterloo, the details of which are explored in the following chapter.

5.3 Summary of Data Collection

This section summarizes the data from the various detectors that were implemented in the study areas. Several vendors were used as each product provided a different hardware solution. For this thesis, confidentially of the vendor systems are maintained by referring to them by letter. The sources of data summarized in this report are as follows:

- Bluetooth data from dedicated Bluetooth detectors in Pilot Area 1 and Highway 401 (System A);
- Bluetooth and Wi-Fi data from a combined Bluetooth-Wi-Fi (hybrid) detector (System B);
- Wi-Fi data from intersection based detectors (System C);
- Traffic puck data; and
- Video data from Region of Waterloo

5.3.1 System A: Bluetooth Detector Data Availability

The Bluetooth detectors were deployed in Pilot Area 1 260 m north of the intersection of Hespeler Road and Pinebush Street and at the intersection. In addition to the data at the study intersection, a separate data file was provided for Bluetooth data on the 401 between Homer Watson and Townline in Cambridge. **Table 5-2** and **Table 5-3** contain the summary of the data availability of the deployed detectors, with the complete list of the availability of the data in **Appendix B**.

Table 5-2 – Summary of System A Bluetooth data on Hespeler Road

Deployment Start Date	March 15, 2016
Deployment End Date	June 28, 2016
Number of days deployed	106
Number of days with missing data	24
Percentage of days with complete data	77.3%

Table 5-3 – Summary of System A data on Highway 401

First Date	March 15, 2016
Last Date	May 18, 2016
Number of days deployed	65
Number of day with missing data	0
Percentage of days with complete data	100%

Note that the term "missing data" means that for a given day the pair of detectors did not provide matched travel times for a substantial period of time (more than 8 hours), with the majority missing data for an entire day. In case of the Hespeler Road detectors they were powered by battery packs, and it is likely that these missing data would be due to the depletion of the batteries. This can be contrasted with the 401 detectors, as they did not depend on batteries for operation, and had no missing days of data.

5.3.2 System B: Combination Bluetooth Wi-Fi Detectors Data Availability

The hybrid detectors were deployed in Pilot Area 2 at two intersections, which are both Hespeler Road and mall accesses. **Table 5-4** contains the summary of the data availability of the deployed detectors, with the complete list of the availability of these data in **Appendix B**.

Table 5-4 – Summary of System B data on Hespeler Road

Deployment Start Date	May 4, 2016
Deployment End Date	July 18, 2016
Number of days deployed	76
Number of day with incomplete data	17
Percentage of days with complete data	77.6%

5.3.3 System C Intersection based Wi-Fi and Traffic Puck Data Availability

The Wi-Fi detectors and traffic pucks remained deployed in the field after the completion of the pilot study. Data were obtained for the time period of February 22 to April 10, 2016. These data were in a raw form which limited the usefulness of the traffic puck data. Although these data were not directly analyzed in this thesis, the data were used to identify days with atypical traffic patterns to derive the algorithm proposed in the next chapter.

5.3.4 Region of Waterloo Video Data

Due to issues with the retention date of the video files there is no video data available for the project.

6.0 Simulation-Based Assessment of Pilot Study Derived Algorithm

The data from the System A detectors in Pilot Area 1 was used to establish the basis for an algorithm that could be used to identify atypical traffic conditions from Bluetooth travel times. This chapter covers the following:

- The analysis that was completed to develop and select the candidate algorithm;
- The simulation experiment that assessed the selected algorithm; and
- The performance of the algorithm from the simulated experiment.

6.1 Development and Selection of Algorithm

The data collected in partnership with the Region of Waterloo was used as the foundation for the development of algorithms that use Bluetooth data to identify when atypical traffic conditions were detected on Hespeler Road. The assessment of the pilot field data was completed as part of the joint project with the Region and is documented in an internal project report. The report identified and assessed several candidate algorithms based on the field historical data. This section of the thesis summarizes the findings of this report.

6.1.1 Selection of Aggregation Interval

For the purpose of implementing a TRPS system the decision interval to identify if atypical conditions exist is very important. For the pilot field study, a 15-minute collection interval was selected for three reasons. The first reason was the fact that TRPS systems are meant to respond to atypical intervals that persist, and having intervals that are short (e.g. 5 minutes) are less stable due to cycle to cycle fluctuations in demand. Secondly, this duration allows for a sufficient amount of Bluetooth data to be collected with weekdays having more than 15 travel times between 6 a.m. and 9 p.m. which would be the time of day when atypical conditions would be of the greatest concern. Third, changing signal timing plans usually imposes some short term disruption to traffic flow as the traffic signals transition to the new signal timing plan. Consequently, changing timing plans too frequently would not improve intersection performance.

6.1.2 Definition of Typical and Atypical Intervals

The terms "typical" and "atypical" were previously defined in the simulation experiments, where the exact time and character of an event was known. However, for the field pilot study, there is no direct way to measure the truth. Therefore, the traffic pucks and loops were used as the data source to identify when atypical traffic conditions occurred.

The selected conventional measurement for the field pilot study was detector occupancy. The occupancy of the midblock southbound Hespeler Road upstream of Pinebush Street showed occupancy could be reasonably used to identify when the approach is congested. This can be seen in **Figure 6-1**, where occupancy has a linear relationship with volume until approximately 10%, at which point increases in occupancy are not associated with an increase in volume. This was interpreted as the point at which the approach becomes saturated.

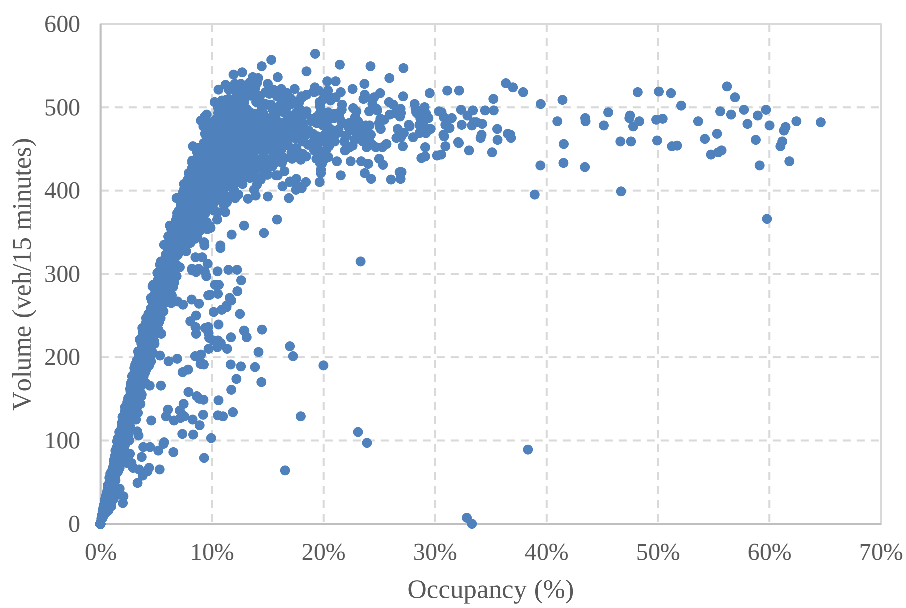

Figure 6-1 – Volume vs. Occupancy at southbound Hespeler Road detectors

A heuristic rule-based algorithm was developed to label each time interval as "atypical" or "typical" on the basis of the detector occupancy measurements.

The algorithm was conceived on the basis that occupancy measurements of the current time interval would be compared to historical measurements for the same time of day. These historical measurements define “typical”. If the current measurement differs sufficiently from these historical measurements, then the current time interval is likely atypical.

The raw measurement for each time interval consisted of the detector occupancy computed over the 15 minute time interval.

For the purposes of identifying atypical conditions we determined the following:

1. Categorize current day as a Weekday (0); Sunday (1); or Saturday (2).
2. Identify historical data. If the current day was a weekday, then the set of historical data consisted of the previous 20 weekdays. If the current day was a Sunday or Saturday, then the historical data consisted of the data for the current and previous time intervals from the same day of week from the previous 8 weeks.
3. The number of historical days for which data were available was recorded.
4. The mean and standard deviation of the 15-minute occupancy measurements were computed on the basis of the historical data. Then the upper and lower 95% confidence limits were computed assuming a Normal distribution.

The heuristic algorithm to identify atypical time intervals was developed iteratively. In each iteration, the candidate labelling algorithm was evaluated by examining the time intervals that were labelled as “atypical” and determining if these labels were appropriate. Note, that no objective measure of the truth existed (i.e. an independent measure of which time intervals were typical or atypical) and consequently, the assessment of the algorithm relied on engineering judgement.

The final version of the heuristic algorithm consisted of three components as follows:

1. Comparison of the current measurement to the historical data:

   The measurement from the current time interval was compared to the 95% upper confidence limits (i.e. mean + 1.96 × standard deviation). It was found that the 95% confidence limit was too restrictive and resulted in an unrealistically large number of time intervals labelled as atypical. An obvious solution would be to use a larger confidence interval (e.g. 98% or 99%). However, due to issues in the implementation of the algorithm in the database, all historical data had been processed to store the 95%

confidence limits and re-computing other confidence limits from the raw data was not possible. Consequently, an alternative approach was adopted in which the historical upper limit of detector occupancy was computed as $\alpha \times 95\%$ CL. Alpha was determined to be equal to 1.1. Time intervals for which the measured occupancy exceeded this historical upper limit were considered unusual.

2. Establishing a baseline value of occupancy:

   The purpose of identifying atypical conditions is to determine when it would be advantageous to switch signal timing plans. As such, it is of much greater interest to only consider those time intervals when the approach is congested or nearing congestion. When traffic demands are very low, there is little benefit to altering signal timing plans. Consequently, the current occupancy measurement also needed to exceed a threshold value in order to be considered atypical. Calibration determined that this threshold should be 10%.

3. Persistence:

   The last element of the algorithm was to examine the temporal persistence of the conditions. The purpose of the labeling was to identify those time periods for which changing traffic signal timing plans would likely be warranted. If the conditions identified in components 1 and 2 were satisfied for a time interval i, and then were not satisfied for the subsequent time interval (i+1), then it was concluded that time interval i was not atypical.

The intervals identified as atypical according to the conventional analysis were considered to be the “truth” for the purposes of evaluating the Bluetooth travel time based algorithms.

6.1.3 Overview of Selected Bluetooth Algorithm

Three algorithms that utilize Bluetooth detector data were proposed as part of the overall project. This thesis focuses on the Rule-Based Algorithm.

Similar to the occupancy-based algorithm several rules were determined based on the collected data. It was found from the review of the field data that the algorithm should be based on the following components:

1. Use median travel time rather than mean travel time as the median is less susceptible to outliers.
2. Determination of historical confidence limits should only use data from time intervals for which a minimum number of travel time measurements were obtained. This would reduce the influence of outliers and measurement errors within individual travel time measurements.
3. Do not declare the current conditions as atypical unless the median travel time exceeds the historical upper limit by a non-trivial amount.

Using these concepts, a heuristic algorithm was calibrated with the following parameters:

- A minimum of 35 Bluetooth measured travel times were obtained;
- The median travel time exceeds the 95% confidence limit computed based on historical data; and
- The ratio of the median travel time to the 95% upper confidence limit ≥ 1.1.

The median travel time was selected over the average travel time, as it was found that the average could be influenced by outliers due to the overall small number of samples in a given observed interval. This is supported by **Figure 6-2**, where there is a strong correlation between the median and average Bluetooth Travel Time, but between 5 and 10 minutes (the region in the red rectangle) there is a higher variation in average travel time.

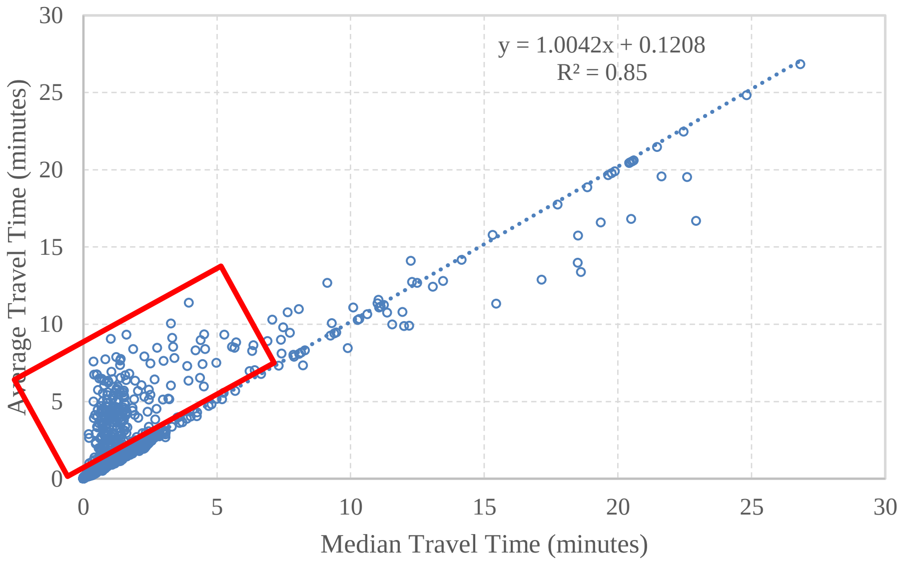

Figure 6-2 – Comparison of Average vs Median Travel Time

The rule-based algorithm and other algorithms were calibrated and evaluated using the collected pilot data. The models were assessed based on the following four possible outcomes:

1. The model labels the interval as normal and the interval is actually normal;
2. The model labels the interval as normal when the interval is actually atypical;
3. The model labels the interval as atypical but the interval is actually normal; and
4. The model labels the interval as atypical and the interval is actually atypical.

For the above, outcomes 1 and 4 represent the correct result from the model, and outcomes 2 and 3 represent erroneous results. Then each of the algorithm's identifications of normal or atypical traffic conditions for a 15-minute interval were compared to the loop detector based identification. The Rule-Based Algorithm was found to correctly identify normal intervals 96% of the time, with only a 4% false alarm rate (when an interval was flagged as atypical, but is normal), however it was only accurate 58% of the time at identifying atypical intervals. However, due to its ability to correctly identify normal conditions, the low false alarm rate, and the simplicity of its operation, the rule-based algorithm was carried forward for assessment from simulated data, which is explored in the next section.

6.2 Algorithm Simulation Experiment Overview and Inputs

With the adoption of the rule-based algorithm as the preferred field-derived method, a simulation experiment was designed based on the field data and information from the Region of Waterloo. A simulation experiment was required to supplement the findings of the pilot study, to address the fact that the truth that was compared to was only an estimate of the traffic conditions. Simulation allows for control of the inputs as well as the outputs, to further test the viability of the algorithm. The results of the simulation can provide a secondary assessment of the proposed algorithm, and provide the opportunity to improve the algorithm before implementing it in the field.

For the experiment, the same simulated network was used as in Experiments 1 and 2, due to the relationship with the Hespeler Road corridor. The same detector configuration was used, with a detector located at the intersection and upstream of the intersection at midblock on the north leg.

For this simulation experiment, there were two data sets required, (1) the historical data, made up of typical operations at the study intersection during a peak period and (2) atypical data, which used the typical data as a base, but then had significant diversion volume.

The historical data set was derived from the TMCs at the study intersection peak periods for 40 theoretical week days. The traffic was generated by taking the base AM peak period vehicle counts on an approach basis for each hour and modifying it using the following procedure:

1. The randomized hourly volume (V_d) was based on the peak hour volume from the turning movement counts (V), assumed to be the mean volumes;
2. The base Volume (V) was adjusted by a coefficient of variation (COV) of 0.087 that was adjusted by a randomized normal standard deviate (z);
3. Z was calculated by using a random number between 0.025 and 0.975, the 95th confidence range of the normal distribution;
4. Thus, the randomized hourly volume can be expressed as V_d = V*COV*Z+V.

This hourly volume was then multiplied by the existing peak hour factor to correctly capture the peaking in the hour. The procedure above allows the total approach volumes to range approximately between 16% lower and 16% higher than the base volumes. The simulation was conducted in the AM peak period, as initial analysis in Synchro demonstrated that there was sufficient capacity for the base conditions, and an increase of this magnitude should not result in an overcapacity movement.

This allowed for a more robust historical data set, as the input volumes to Vissim were randomly generated based on a typical day of operations. In addition to the pre-processing of the input volumes, each run in Vissim has a different random seed which further increases the variability of the historic data set. The historical runs were completed in Vissim and then processed in BlueSynthesizer to form the basis of the historical Bluetooth travel times.

The atypical data set was based on the AM peak period as well, but assumed a significant increase in the southbound left turn volumes. This movement was selected for the simulation experiment as it was consistent with the previous simulation experiments, and the Region of Waterloo had identified it as target movement for TRPS due to the potential for Highway 401 diversion traffic to travel through the study intersection. In addition to expressing interest in this movement from a system perspective, the Region provided an estimate of the expected diversion, based on their experience. Their estimate for an incident resulting in significant diversion on Highway 401 was an additional 1130 vehicles/hour attempting to turn left at Pinebush Street to avoid delay on the highway. From preliminary simulation analysis, it was found that the duration of the diversion volume could not be for a full hour, as it would result in complete gridlock. To ensure that an atypical condition could be recorded and recoverable without intervention (the simulation does not have a way to implement a more appropriate signal timing plan) the atypical volume was only modelled for 30 minutes in the 3-hour simulation period.

The historical data set was considered to be the base scenario. In addition to this case, there were two diversion scenarios, namely *heavy diversion* and *moderate diversion*. The heavy diversion scenario consisted of a diversion demand of 1130 vph (565 vehicles in the 30 minute diversion event). The moderate diversion scenario consisted of a diversion demand of 800 vph (400 vehicles in the 30 minute diversion event). The decision to include a moderate level of diversion was to ensure that the generated congestion from the Region's recommended turning was not unfairly increasing the algorithm's ability to identify atypical conditions. The duration of the atypical events was 30 minutes, and the start time of the event was varied in the simulation. The diversion started at either the 1-hour, 1.5-hour, or 2-hour point in the simulation. Varying the start time was done to limit the influence the base traffic would have on the atypical event. The event was started in the middle of the simulation period to demonstrate that that there was enough time for the queues to dissipate after the diversion event ended. This showed that overall there was sufficient capacity at the signal, and the algorithm was not simply reporting travel times from a gridlocked network. The scenarios are summarized in **Table 6-1**. Similar to the previous experiments, 15-minutes of warm-up time was included in the model, and 10% market penetration of Bluetooth detectors was maintained.

Table 6-1 – Summary of Atypical Scenarios IDs

Start Time	Diversion Scenario	
	Moderate	Heavy
1 hour	1	2
1.5 hour	3	4
2 hour	5	6

With a 30-minute duration and the 6 atypical events, it was expected that the algorithm would identify at least 12 intervals as “atypical”. It is expected that the algorithm would also identify time intervals directly following the diversion event as atypical due to time required to dissipate the overcapacity movement. However, these subsequent intervals were of limited interest, because if the system was active, instead of having the atypical scenario persist as it dissipated, the system would respond to the event by changing the signal timing plans.

6.3 Algorithm Experiment Results

With the completion of the Vissim simulation, the data were processed in BlueSynthesizer to produce 15-minute interval travel times for the 40 historical simulation runs and the six simulation runs representing the diversion scenarios (i.e. atypical periods). The data from one of the simulation runs representing a historical day can be seen in **Figure 6-3**. The figure shows the mean, 5th and 95th percentile travel times for each 15 minute interval of the selected simulation. In addition, the number of Bluetooth travel times for each interval were reported. The average interval travel time is fairly consistent at approximately 50 seconds. The 95th percentile travel time is approximately 100 seconds, while the 5th percentile is 20 seconds. The upper and lower percentile travel times can be seen as representing the experience of a particular vehicle, as the 5th percentile would represent a vehicle that is not impeded by the traffic signal (i.e. free-flow) and the 95th percentile would represent a vehicle that stopped at the signal. The number of Bluetooth travel times in a 15-minute interval ranges from 9 to 37. This number of travel times is explored in more detail later in the section.

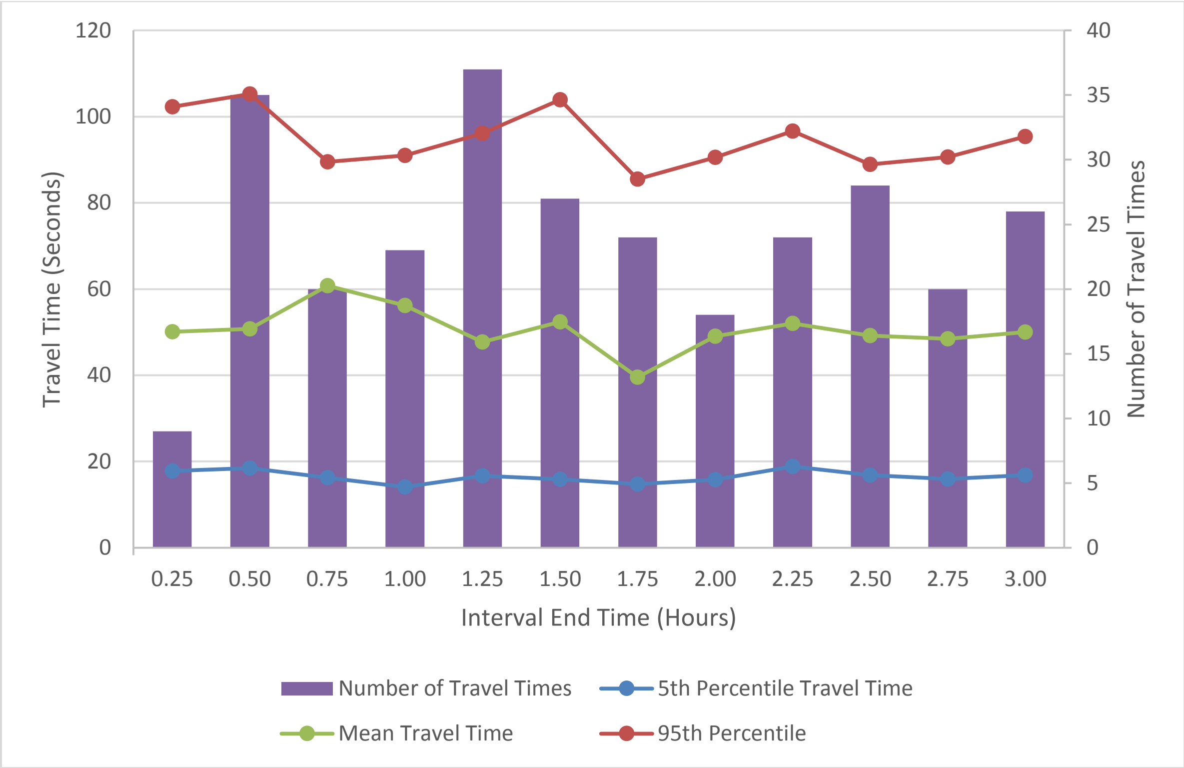

Figure 6-3 – Typical Bluetooth Travel Time for historical data Set

All of the historical periods (40 total) were then aggregated for each 15 minute interval. The mean travel time for each 15-minute interval was calculated, as well as the 95th percentile confidence limit. The average number of travel times for each interval was also reported. The results of this analysis can be seen in **Table 6-2** and **Figure 6-4**.

Table 6-2 – Summary of historical Bluetooth data by interval

Start of Interval (minute)	End of Interval (minute)	Mean Bluetooth Travel Time (seconds)	95th Percentile Mean Bluetooth Travel Time (seconds)	Average Number of Bluetooth Travel Times
0	15	51	63	19
15	30	50	58	34
30	45	50	61	29
45	60	50	61	33
60	75	54	61	35
75	90	50	56	33
90	105	51	59	28
105	120	47	56	25
120	135	50	60	26
135	150	47	53	26
150	165	50	58	21
165	180	48	56	23

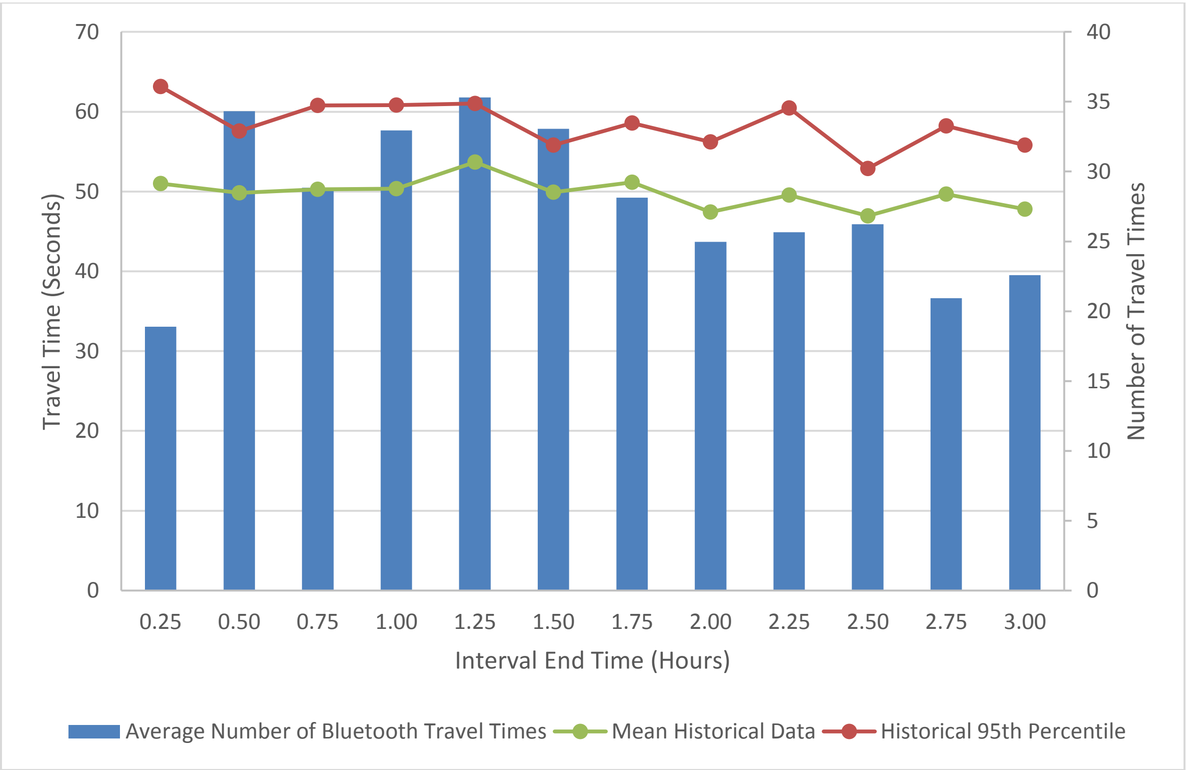

Figure 6-4 – Aggregated historical Bluetooth data by time interval

As can be seen in the above table and chart, the travel time is consistent across the peak period, the mean Bluetooth travel time is approximately 50 seconds, and the 95th percentile confidence limit is approximately 60 seconds. With the 10% increase required in the rule-based algorithm, any interval with a median Bluetooth travel time above approximately 66 seconds would be considered an atypical interval. The average number of Bluetooth travel times ranged from 19 to 35. This is notable, as the field data appears to exceed the number of travel times produced by simulation. It is hypothesized that the selected 10% level of market penetration is conservative when compared to the reality on Hespeler Road. Since for the historical data the average number of travel times in a 15-minute interval is 29, the number of required travel times for the algorithm was reduced to 25, from the 35 recommended from the pilot data. Due to the fact that the simulation was a controlled environment, there are no outlier travel times generated, therefore the reduction in the required number of travel times does not have a great impact on the accuracy of the measured travel times. In other words, it is not possible for vehicles to depart the travel path, and as such, every travel time would be valid.

Using the aggregated historical data and the modified algorithm, the atypical results were compared to the historical data on an interval basis for each of the atypical periods. **Figure 6-5 (a)** illustrates the median travel time for each 15-minute interval compared to the aggregated historical data for Diversion Scenario 1 (moderate diversion beginning 1-hour into the simulation). The number of travel times are included in **Figure 6-5 (b)** to confirm if the required threshold of travel times has been met.

From the below plots, it can be seen that the identification of atypical conditions occurs 1.25 hours into the simulated run. As the simulated diversion event begins at the 1-hour mark, this timeframe is expected, as it is one interval after the diversion volume begins. The travel times remain above the switch threshold (1.1 multiplied by the 95th percentile confidence limit of a given interval) for the next four intervals, which was expected, as the diverting traffic did not stop until 1.5 hours into the simulation. The two intervals exceeding the threshold for the intervals following the end of the simulated diversion were expected, as these intervals represent the recovery of the signal operations. The recovery of operations at the signal occurred without any intervention from the software, due to the fact that the measurements were not occurring in real-time. It should be noted, that although the interval ended at the 1 hour mark appears to exceed the threshold, due to the required number of travel times in an interval (25), the interval is not identified as atypical.

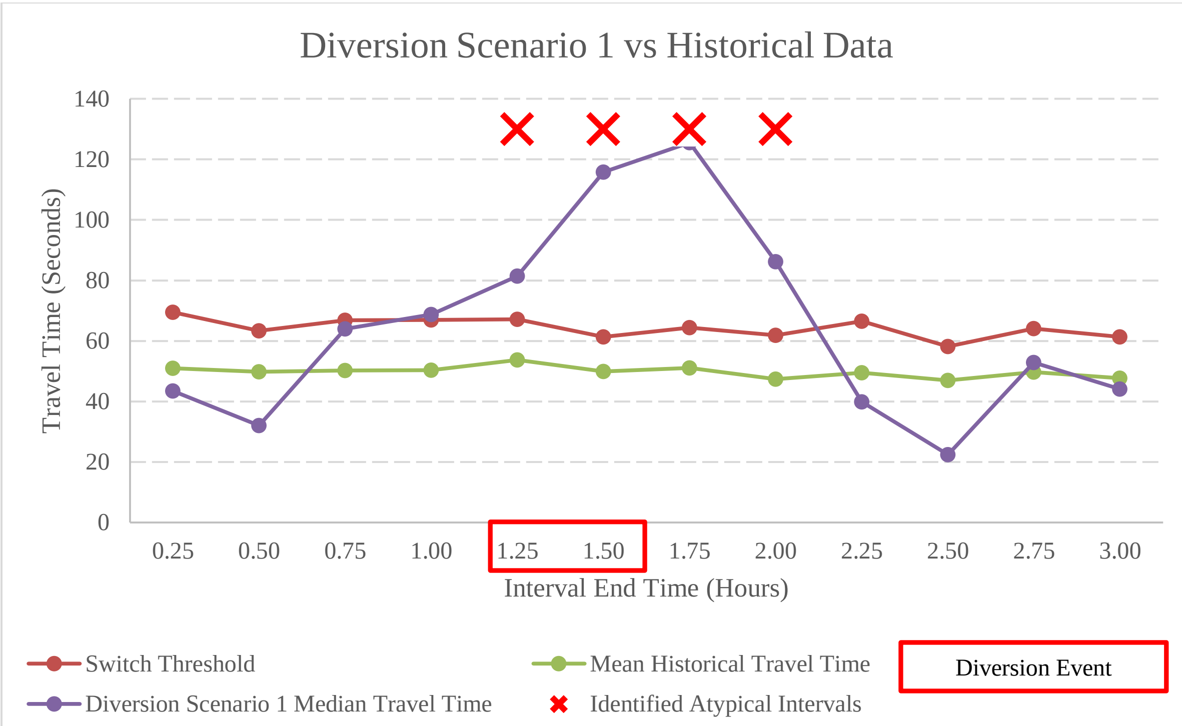

Figure 6-5 (a) – Diversion Scenario 1 travel times vs historical data set

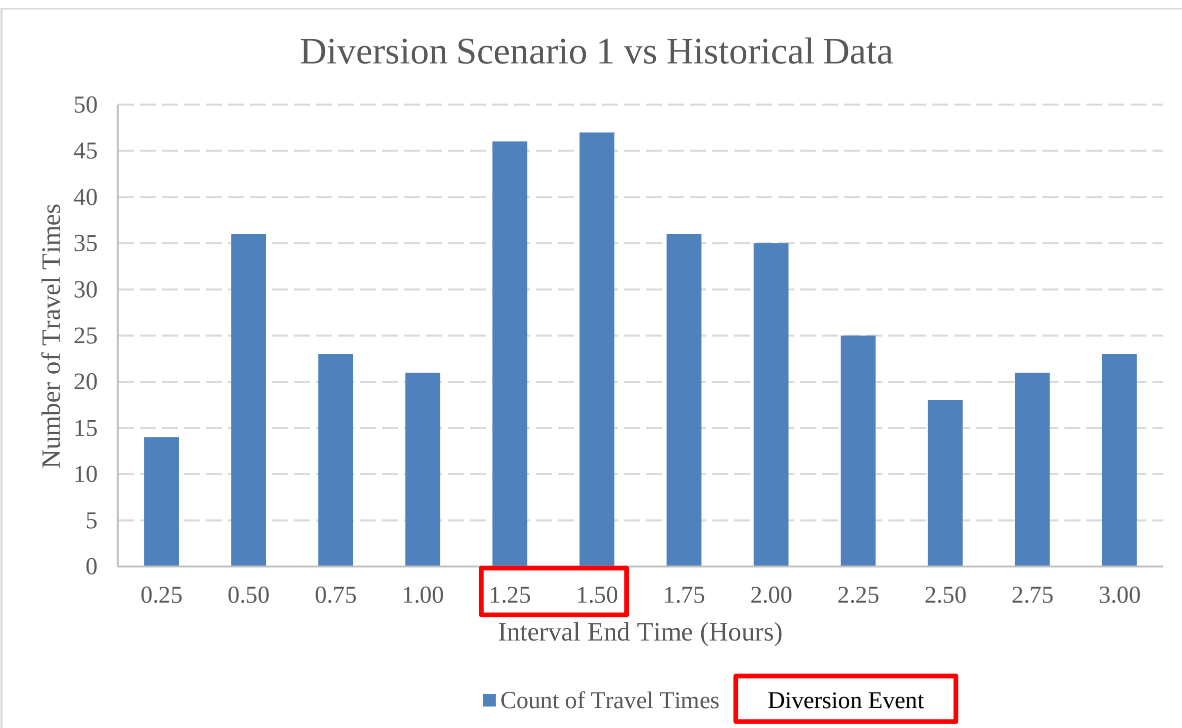

Figure 6-6 (b) – Diversion Scenario 1 count of travel times by interval end

The remaining diversion scenario plots can be seen in **Appendix C**, which are similar to the above plot. Notable about the heavy diversion scenarios is the fact that their travel times are typically higher than that of the moderate one, and the recovery time is significantly longer. The rule-based algorithm correctly identified all of the atypical intervals from the simulated data.

6.4 Algorithm Experiments Conclusions

From the simulated test of the rule-based algorithm it appears that the Bluetooth travel times can be effectively used to identify atypical intervals based on known diversion pattern. This supports what was found in the pilot study, as a sufficiently populated historic data set provides a good comparison point for determining which travel times are reasonable. Though beyond the scope of this thesis, it is recommended that the effectiveness of using this algorithm for TRPS, be evaluated within a simulation environment by integrating the BlueSynthesizer software, the proposed algorithm, and the TPRS logic within a suitable microscopic traffic simulation model (such as VISSIM). This would provide the ability to determine if there is an improvement in the recovery time of the intersection when compared to the conventional control.

7.0 Conclusions

This research has found that the use of Bluetooth detectors as an alternative source for data in a TRPS signal control system shows promise. Bluetooth detectors could provide the ability to monitor traffic conditions at and in the proximity of signalized intersections in a way that can provide valuable information to signal controllers.

This research explored the use of simulated and field Bluetooth data to determine the traffic states and identify when traffic conditions would benefit from a signal plan change. This chapter presents the main conclusions from the research.

7.1 Recommended Measures of Performance

Three main MOPs were considered for Bluetooth measurements, (1) travel time, (2) dwell time, and (3) number of hits. It was found from the simulated data, that the most reliable MOP when compared to the true travel time was the Bluetooth travel time, with measurement errors associated with dwell time and number of hits limiting their usefulness. This was further confirmed in the pilot field study.

7.2 Simulated Assessment of the MOPs

Vissim models were developed based on the Hespeler Road corridor to provide a test environment for the proposed MOPs. The control over the inputs and the ability to accurately measure the true travel time allowed for analysis of each MOP without the influence of outliers. As discussed in the previous section, the first round of simulation experiments identified the Bluetooth travel time had the greatest potential at identifying true traffic conditions. The second experiment was a preliminary investigation into the ability for the Bluetooth detectors to detect a change in travel time. It was found that for the proposed scenarios the simulated Bluetooth data could be used to distinguish between uncongested and congested traffic states.

7.3 Field Pilot Study

In partnership with the Region of Waterloo a field pilot study was conducted on the Hespeler Road corridor. The Bluetooth and conventional detectors placements were informed by the simulation work. The pilot study was conducted for a several month period to allow for the collection of Bluetooth and conventional detector data at several locations ago the corridor. The collected data were used to develop candidate algorithms for the identification of atypical traffic conditions, which is reviewed in the following section.

7.4 Assessment of Rule-Based Algorithm

The conventional and Bluetooth traffic data were used by the field project team to develop several algorithms that were assessed against the collected pilot data. From this investigation, it was found that a rule-based algorithm was the most accurate at determining when there was congestion present according to the conventional detectors.

Using the algorithm developed from the pilot data, a simulation experiment was conducted to determine how the algorithm would function without the influence of outlier travel times and with known true traffic conditions. From these experiments it was found that the algorithm could identify periods of congestion caused by unexpected traffic variations. However, these simulations were conducted off-line, preventing the resolution of the atypical events using an alternative signal timing plan. This leads to the recommendations for further research.

7.5 Future Research

This research demonstrated the potential of a novel application of Bluetooth detectors as a data source in traffic engineering. Future research related to the implementation of this system are as follows:

- This thesis focused on the scenario where Bluetooth detectors were placed at the study intersection and upstream at mid-block. However, it is often more economical to deploy Bluetooth detectors at signalized intersections rather than mid-block, largely because of access to electric power and communications infrastructure, as well as suitable enclosures. As a result, it is recommended to investigate the influence of detector placement (i.e. at intersections vs midblock) and the presence of intermediate signalized intersections.
- An application could be developed to interact with Vissim in real-time to assess the effectiveness of the candidate algorithm at identifying and correcting atypical conditions.

This application would provide greater confidence before conducting a field pilot test of the system.

- For the selected study corridor, although the timing of the atypical events was not known, the general pattern was relatively well understood due to the proximity to the highway. Conducting simulations with more variations in the atypical demands could demonstrate how the system responds to several different scenarios.
- Once the candidate algorithm has been assessed further, another pilot study should be conducted with a simple TRPS system in place to determine how effective the Bluetooth detectors are at identifying and correcting atypical congestion in the field.

References

Abbas, M. M., & Abdelaziz, S. (2009) Evaluation of traffic responsive control on the Reston Parkway arterial network. Virginia Transportation Research Council, Report No. VTRC 09-CR6.

Abbas, M. M., & Sharma, A. (2004) configuration of traffic-responsive plan selection system parameters and thresholds: robust Bayesian approach. Civil Engineering Faculty Publications. Paper 16. http://digitalcommons.unl.edu/civilengfacpub/16

Abbas, M. M., Chaudhary, N. A., Sharma, A., Venglar, S. P., & Engelbrecht, R. J. (2004). Methodology for determination of optimal traffic responsive plan selection control parameters.

Balke, K. N., Rao, K. S., Brehmer, C. L., Texas Transportation Institute, & Texas. Department of Transportation. (1997). Guidelines for implementing traffic responsive mode in TxDOT closed-loop traffic signal systems. Texas Transportation Institute, Texas A & M University System.

Barceló, J., Montero, L., Marqués L., & Carmona, C. (2010) Travel time forecasting and dynamic origin-destination estimation for freeways based on Bluetooth traffic monitoring. Transportation Research Record: Journal of the Transportation Research Board, 2175, 19-27.

City of Calgary. Bluetooth travel time system. Retrieved November 7, 2017, from http://www.calgary.ca/Transportation/Roads/Pages/Traffic/Traffic-management/Bluetooth-detection-system.aspx

Gordon, R. L., & Tighe, W. (2005). Traffic control systems handbook. Washington, DC: U.S. Dept. of Transportation, Federal Highway Administration, Office of Operations.

Haghani, A., Hamedi, M., Sadabadi, K., Young, S., & Tarnoff, P. (2010). Data collection of freeway travel time ground truth with Bluetooth sensors. Transportation Research Record: Journal of the Transportation Research Board, 2160(1), 60-68.

Haghani, A., & Hamedi, M. (2013). Application of Bluetooth technology in traffic detection, surveillance and traffic management. Journal of Intelligent Transportation Systems: Technology, Planning and Operations, 17(2), 107-109.

Hart-Bishop, J., Hellinga, B., & Zarinbal, A. (2016). Advanced Traffic Signal Control using Bluetooth/Wi-Fi Detectors. Kelowna 2016 - CITE Annual Meeting and Conference - Technical Compendium.

Hu, Y. (2013). Short-term prediction of freeway travel times using data from Bluetooth detectors. (Doctoral, University of Waterloo).

iTrans Consulting Inc. (2006) Costs of non-recurrent congestion in Canada final report. Transport Canada Economic Analysis, Ottawa.

Kay, J. L., Henry, R. D., Smith, S. A., & United States. Federal Highway Administration. Traffic Systems Division. (1975). Locating detectors for advanced traffic control strategies: handbook Department of Transportation. Federal Highway Administration, Office of Research, Traffic Systems Division.

Koonce, P., Rodegerdts, L., Lee, K., Quayle, S., Beaird, S., Braud, C., & Urbanik, T. (2008). Traffic signal timing manual. (No. FHWA-HOP-08-024).Federal Highway Administration.

Moghaddam, S., & Hellinga, B. (2013a). Evaluating the performance of algorithms for the detection of travel time outliers. Transportation Research Record: Journal of the Transportation Research Board, 2338, 67-77.

Moghaddam, S., & Hellinga, B. (2013b). Quantifying measurement error in arterial travel times measured by Bluetooth detectors. Transportation Research Record: Journal of the Transportation Research Board, 2395, 111-122.

Moghaddam, S., & Hellinga, B. (2014). Real-time prediction of arterial roadway travel times using data collected by Bluetooth detectors. Transportation Research Record: Journal of the Transportation Research Board, 2442, 117-128.

National Research Council (U.S.). Transportation Research Board. (2010). HCM 2010: Highway capacity manual Transportation Research Board.

Nelson, E., Abbas, M., Shoup, G., Bullock, D., & Gallagher, R. (2000). Development of closed loop system evaluation procedures.

Nelson, E., Abbas, M., Shoup, G., Bullock, D., & Gallagher, R. (2000). Development of closed loop system evaluation procedures. Joint Highway Research Program, Purdue University.

Quayle, S., Koonce, P., DePencier, D., & Bullock, D. (2010). Arterial performance measures with media access control readers. Transportation Research Record: Journal of the Transportation Research Board, 2192(1), 185-193.

Woods, D.,L, & Rowan, N.,J. (1995). Detector location for computerized arterial street sampling detectors. Research Report ; 1392-6.

Vo, T. (2011) An investigation of Bluetooth technology for measuring travel times on arterial roads a case study on Spring street. (Master's Thesis, Georgia Institute of Technology, Atlanta).

Zarinbal, A. (2017). Adaptive traffic signal optimization using Bluetooth data. (Doctoral, University of Waterloo).

Appendix A: Turning Movement Count Validation of Vissim Model

This appendix summarizes the steps taken to calibrate the Highway 24 / Hespeler Road corridor. AM Base Model, and does so by comparing the simulation outputs to the data that were used for the inputs. The calibration that was performed was based on the intersection volumes on a per movement basis. The reason that the comparison was conducted by each movement is due to the way that the vehicles are inputted into VISSIM, which has the volumes entered on the perimeter of the network. This results in most of the model's northbound and southbound movement volumes dependant on the perimeter volumes rather than specifying the volume for those movements.

In order to determine the effectiveness of the use of static vehicle routes for populating the network, vehicle counters were placed at each signalized intersection for all movements. These vehicle counts were then compared to the hourly volumes from the Turning Movement Counts (TMCs). The VISSIM volumes were plotted against the TMC volumes to determine the overall fit of the data, with the preferred result being a straight line with a slope of 1 (the "Centerline"). The plot can be seen in **Figure A-1**, which was the second plot constructed after outliers caused by model coding errors were identified and corrected.

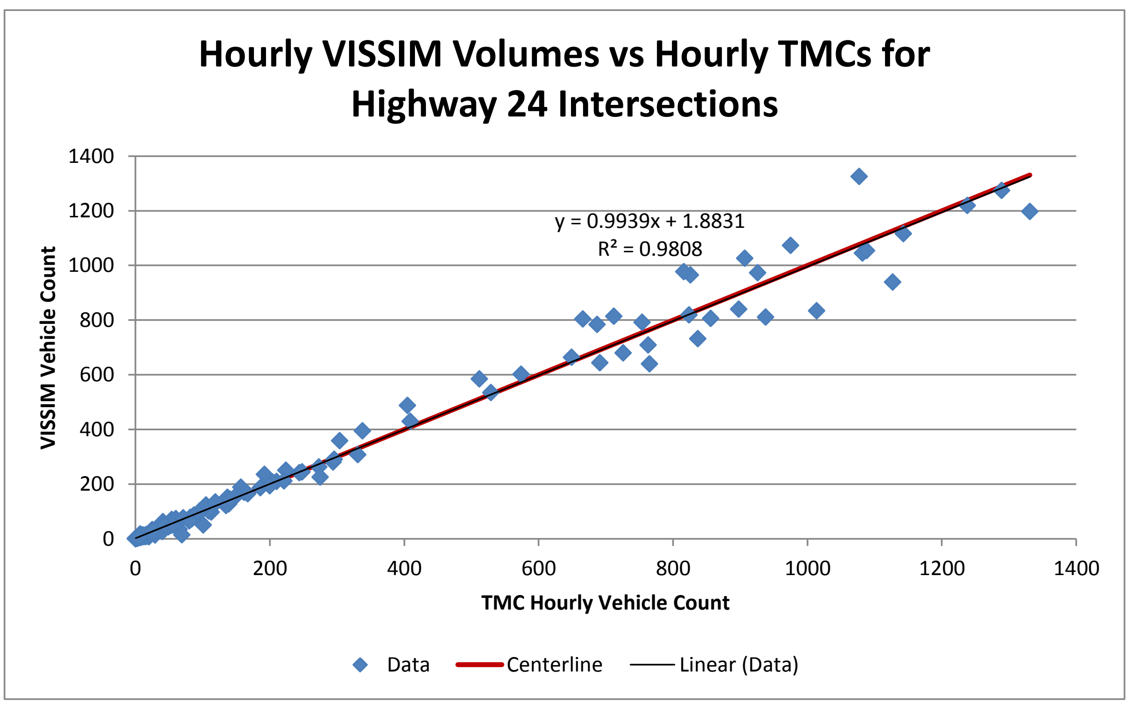

Figure A-1 – Plot of TMC volumes vs. VISSIM volumes

The equation of the Excel trendline can be seen on the figure and it has the very high R^2-value of 0.981, which indicates that the outputs of the VISSIM model are very close to the TMC counts which were used as its inputs, even for the movements that are not part of the perimeter.

However, it should be noted that on the right-side of the plot the data points are further from the centerline. In order to examine which movements were deviating from the TMC counts, the data was filtered by percent difference and actual difference, with values of 10% and 20 vehicles respectively. These thresholds were chosen as it appeared to result in a reasonable pool of movements, as only using one or the other would result in some minor movements being included (such as a right-turn with a simulated volume of 2 and a TMC volume of 1, there would be a 100% difference, but this does not indicate a poor fit). This resulted in 26 movements being identified and they are summarized in **Table A-1**, where the orange values indicted that the VISSIM volumes were greater than the TMCs and the blue values indicted that the TMC volumes were greater than the VISSIM volumes.

Note that of the 26 identified movements, only 2 of the movements are perimeter movements (the WBR at Hwy 401 and the NBL at Hwy 8), which indicates that for the most part VISSIM accurately reproduces the movement volumes using the volume input and static routing decision at the perimeter of the network. The 2 movements that have a larger difference than the stated thresholds can be attributed to the randomness in the model due to the fact that the static route is a simple percentage chance of a vehicle taking any particular movement

The remaining 24 movements in the table are likely then caused by the variation in the TMCs (as they were collected across several years) coupled with the variation introduced by VISSIM's route assignment. This means that the model performed well and that if the inputs were improved the differences between the TMC and the VISSIM volume would also be reduced.

However, it does not appear that the variance between the modelled volume and observed would result in a problem for the modelled movements, as the maximum difference over the hour is 248 vehicles, which is not that many vehicles for a movement when considered over an hour (in the case of a thru movement, which is where vehicle differences are larger).

The main concern regarding the difference in vehicles was for the left-turn movements as an in some cases even a small difference in volumes can result in significant delay, however from observing the model simulation the differences that are reported in the table do not appear to have a negative impact on the overall quality of the model.

Table A-1: Summary of flagged turning movements

Intersection	Movement	TMC Volume	VISSIM Volume	Percent Difference	Difference
Hwy 24 & 401 WB	WBR*	224	250	-11.6%	-26
Hwy 24 & 401 WB	NBR	405	487	-20.2%	-82
Hwy 24 & 401 WB	NBT	1077	1325	-23.0%	-248
Hwy 24 & 401 EB	SBT	826	965	-16.8%	-139
Hwy 24 & 401 EB	NBT	907	1026	-13.1%	-119
Hwy 24 & Pinebush/Eagle	SBR	338	394	-16.6%	-56
Hwy 24 & Pinebush/Eagle	SBT	816	977	-19.7%	-161
Hwy 24 & Pinebush/Eagle	SBL	304	358	-17.8%	-54
Hwy 24 & Pinebush/Eagle	NBT	765	640	16.3%	125
Hwy 24 & Petsmart	SBT	975	1073	-10.1%	-98
Hwy 24 & Petsmart	NBT	938	811	13.5%	127
Hwy 24 & Burger King	NBT	1014	834	17.8%	180
Hwy 24 & Sheldon/Langs	SBR	41	62	-51.2%	-21
Hwy 24 & Sheldon/Langs	SBT	712	814	-14.3%	-102
Hwy 24 & Sheldon/Langs	SBL	157	188	-19.7%	-31
Hwy 24 & Sheldon/Langs	NBT	837	732	12.5%	105
Hwy 24 & Sheldon/Langs	NBL	65	34	47.7%	31
Hwy 24 & Part Source	NBT	1127	939	16.7%	188
Hwy 24 & Bishop	SBL	101	50	50.5%	51
Hwy 24 & Dunbar	SBL	69	14	79.7%	55
Hwy 24 & Can-Amera	SBT	666	804	-20.7%	-138
Hwy 24 & Munch/Isherwood	SBT	687	784	-14.1%	-97
Hwy 24 & Avenue/Jaffray	NBT	1331	1197	10.1%	134
Hwy 24 & Hwy 8	SBT	512	585	-14.3%	-73
Hwy 24 & Hwy 8	SBL	192	235	-22.4%	-43
Hwy 24 & Hwy 8	NBL*	275	225	18.2%	50

Appendix B: Summary of Pilot Study Bluetooth Data Availability

This Appendix outlines the data that was available from the two Bluetooth systems deployed for the pilot study. The status has been summarized as by the following:

- Y = Complete (data available for the compete or the majority of the day);
- P = Partial (data available for part of the day);
- N = No data available;
- N/A = Device not in the field on this day (i.e. not yet deployed or already removed)

The below table is for the availability of System A for both Hespeler Road and Highway 401.

Date	System A Travel Times	
	Hespeler Road	Highway 401
15-Mar-16	Y	Y
16-Mar-16	Y	Y
17-Mar-16	Y	Y
18-Mar-16	Y	Y
19-Mar-16	Y	Y
20-Mar-16	N	Y
21-Mar-16	Y	Y
22-Mar-16	Y	Y
23-Mar-16	Y	Y
24-Mar-16	Y	Y
25-Mar-16	Y	Y
26-Mar-16	Y	Y
27-Mar-16	N	Y
28-Mar-16	Y	Y
29-Mar-16	N	Y
30-Mar-16	N	Y
31-Mar-16	Y	Y
01-Apr-16	Y	Y
02-Apr-16	Y	Y
03-Apr-16	N	Y
04-Apr-16	Y	Y
05-Apr-16	P	Y
06-Apr-16	Y	Y
07-Apr-16	N	Y

Date	System A Travel Times	
	Hespeler Road	Highway 401
08-Apr-16	N	Y
09-Apr-16	Y	Y
10-Apr-16	Y	Y
11-Apr-16	N	Y
12-Apr-16	Y	Y
13-Apr-16	Y	Y
14-Apr-16	Y	Y
15-Apr-16	N	Y
16-Apr-16	Y	Y
17-Apr-16	Y	Y
18-Apr-16	Y	Y
19-Apr-16	Y	Y
20-Apr-16	Y	Y
21-Apr-16	Y	Y
22-Apr-16	Y	Y
23-Apr-16	Y	Y
24-Apr-16	Y	Y
25-Apr-16	Y	Y
26-Apr-16	Y	Y
27-Apr-16	Y	Y
28-Apr-16	Y	Y
29-Apr-16	Y	Y
30-Apr-16	Y	Y
01-May-16	Y	Y

Date	System A Travel Times	
	Hespeler Road	Highway 401
02-May-16	Y	Y
03-May-16	Y	Y
04-May-16	Y	Y
05-May-16	Y	Y
06-May-16	Y	Y
07-May-16	Y	Y
08-May-16	Y	Y
09-May-16	Y	Y
10-May-16	Y	Y
11-May-16	Y	Y
12-May-16	Y	Y
13-May-16	Y	Y
14-May-16	Y	Y
15-May-16	Y	Y
16-May-16	Y	Y
17-May-16	Y	Y
18-May-16	Y	Y
19-May-16	Y	N and N/A
20-May-16	Y	N/A
21-May-16	Y	N/A
22-May-16	Y	N/A
23-May-16	Y	N/A
24-May-16	Y	N/A
25-May-16	Y	N/A
26-May-16	Y	N/A
27-May-16	Y	N/A
28-May-16	Y	N/A
29-May-16	Y	N/A
30-May-16	Y	N/A
31-May-16	Y	N/A
01-Jun-16	Y	N/A
02-Jun-16	Y	N/A
03-Jun-16	Y	N/A
04-Jun-16	Y	N/A

Date	System A Travel Times	
	Hespeler Road	Highway 401
05-Jun-16	N	N/A
06-Jun-16	N	N/A
07-Jun-16	N	N/A
08-Jun-16	N	N/A
09-Jun-16	N	N/A
10-Jun-16	N	N/A
11-Jun-16	N	N/A
12-Jun-16	N	N/A
13-Jun-16	N	N/A
14-Jun-16	N	N/A
15-Jun-16	N	N/A
16-Jun-16	N	N/A
17-Jun-16	N	N/A
18-Jun-16	Y	N/A
19-Jun-16	Y	N/A
20-Jun-16	Y	N/A
21-Jun-16	Y	N/A
22-Jun-16	Y	N/A
23-Jun-16	N	N/A
24-Jun-16	Y	N/A
25-Jun-16	Y	N/A
26-Jun-16	Y	N/A
27-Jun-16	Y	N/A
28-Jun-16	Y	N/A

The following table is for System B deployed on Hespeler Road.

Date	System B Travel Times
4-May-16	P
5-May-16	Y
6-May-16	Y
7-May-16	Y
8-May-16	Y
9-May-16	Y
10-May-16	Y
11-May-16	Y
12-May-16	Y
13-May-16	Y
14-May-16	Y
15-May-16	Y
16-May-16	Y
17-May-16	Y
18-May-16	Y
19-May-16	Y
20-May-16	Y
21-May-16	Y
22-May-16	Y
23-May-16	Y
24-May-16	Y
25-May-16	Y
26-May-16	Y
27-May-16	Y
28-May-16	Y
29-May-16	Y
30-May-16	Y
31-May-16	Y
1-Jun-16	Y
2-Jun-16	Y
3-Jun-16	Y
4-Jun-16	Y
5-Jun-16	Y

Date	System B Travel Times
6-Jun-16	Y
7-Jun-16	P
8-Jun-16	N
9-Jun-16	N
10-Jun-16	N
11-Jun-16	N
12-Jun-16	N
13-Jun-16	N
14-Jun-16	N
15-Jun-16	N
16-Jun-16	N
17-Jun-16	P
18-Jun-16	Y
19-Jun-16	Y
20-Jun-16	Y
21-Jun-16	Y
22-Jun-16	Y
23-Jun-16	Y
24-Jun-16	Y
25-Jun-16	Y
26-Jun-16	Y
27-Jun-16	Y
28-Jun-16	Y
29-Jun-16	Y
30-Jun-16	Y
1-Jul-16	Y
2-Jul-16	Y
3-Jul-16	Y
4-Jul-16	Y
5-Jul-16	Y
6-Jul-16	P
7-Jul-16	N
8-Jul-16	P

Date	System B Travel Times
9-Jul-16	Y
10-Jul-16	P
11-Jul-16	Y
12-Jul-16	Y
13-Jul-16	Y
14-Jul-16	Y
15-Jul-16	Y
16-Jul-16	Y
17-Jul-16	Y
18-Jul-16	P

Appendix C: Additional Bluetooth Algorithm Test Plots

This appendix provides the remaining diversion scenario plots. The figures for each diversion scenario are listed below:

- **Figure C-1 (a)** & **(b)** Diversion Scenario 2, heavy diversion beginning at 1.0 hours into the simulation;
- **Figure C-2 (a)** & **(b)** Diversion Scenario 3, moderate diversion beginning at 1.5 hours into the simulation;
- **Figure C-3 (a)** & **(b)** Diversion Scenario 4, heavy diversion beginning at 1.5 hours into the simulation;
- **Figure C-4 (a)** & **(b)** Diversion Scenario 5, moderate diversion beginning at 2.0 hours into the simulation; and
- **Figure C-5 (a)** & **(b)** Diversion Scenario 6, heavy diversion beginning at 2.0 hours into the simulation.

Figure C-1 (a) – Diversion Scenario 2 travel times vs historical data set

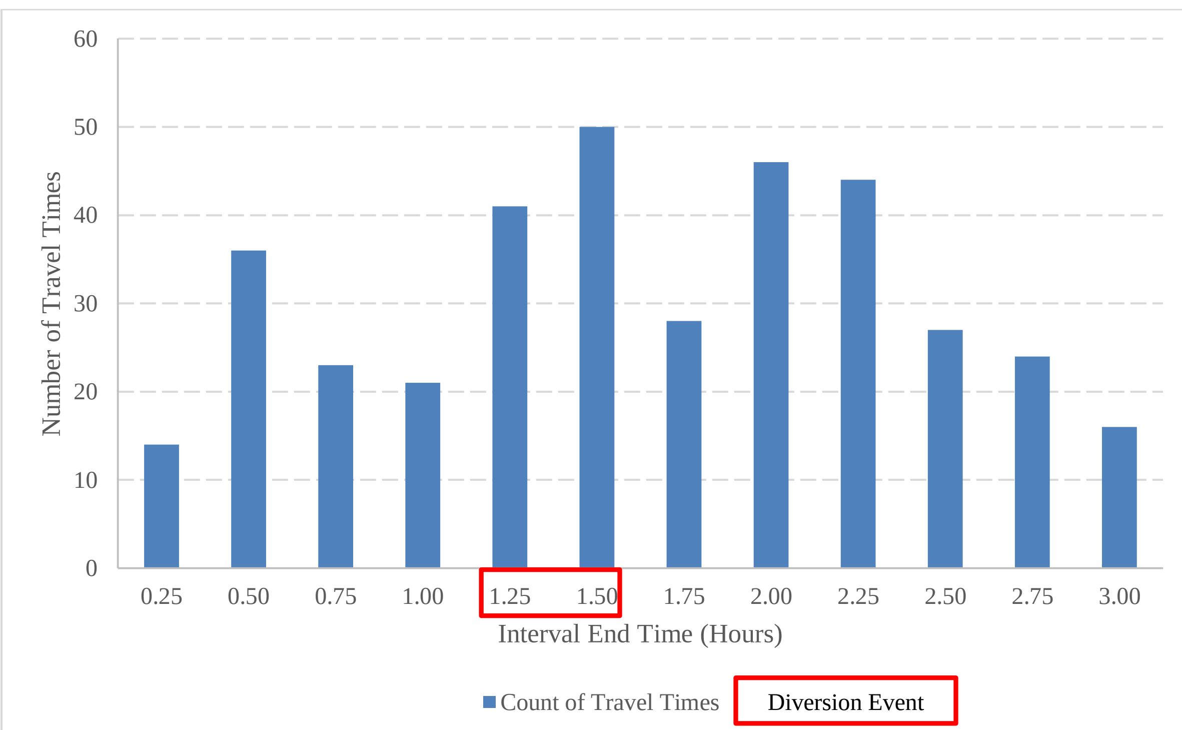

Figure C-1 (b) – Diversion Scenario 2 count of travel times by interval end

Figure C-2 (a) – Diversion Scenario 3 travel times vs historical data set

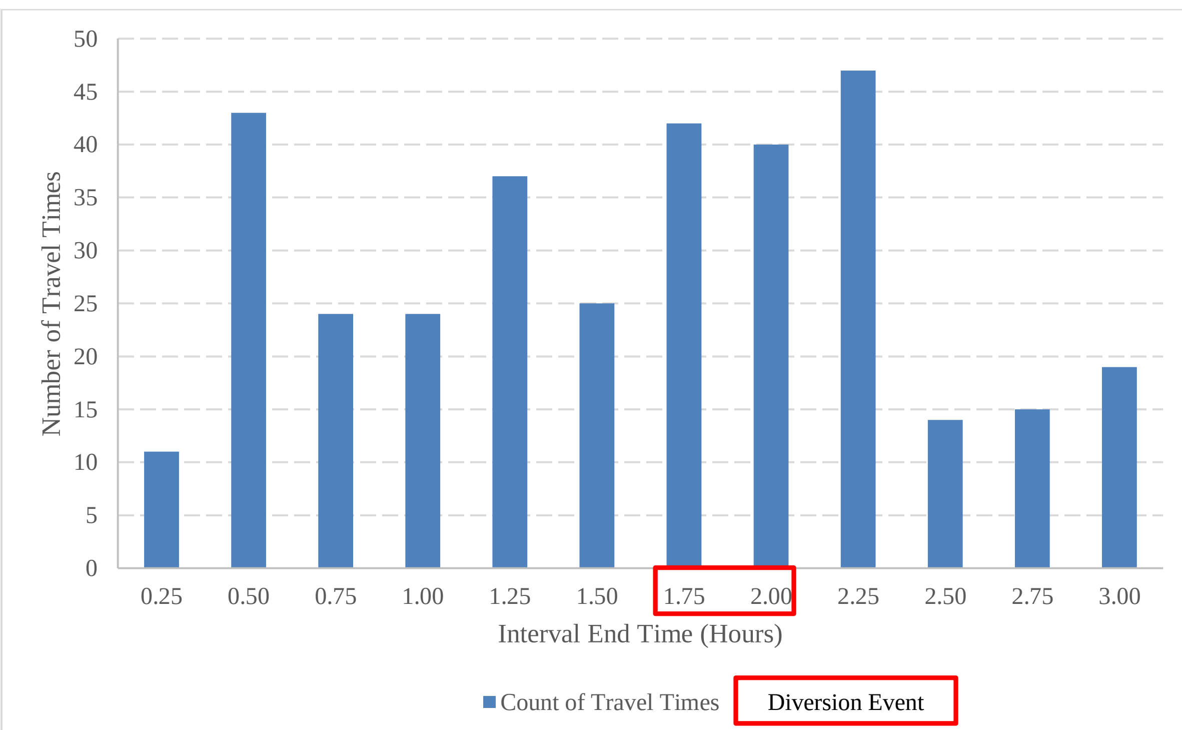

Figure C-2 (b) – Diversion Scenario 3 count of travel times by interval end

Figure C-3 (a) – Diversion Scenario 4 travel times vs historical data set

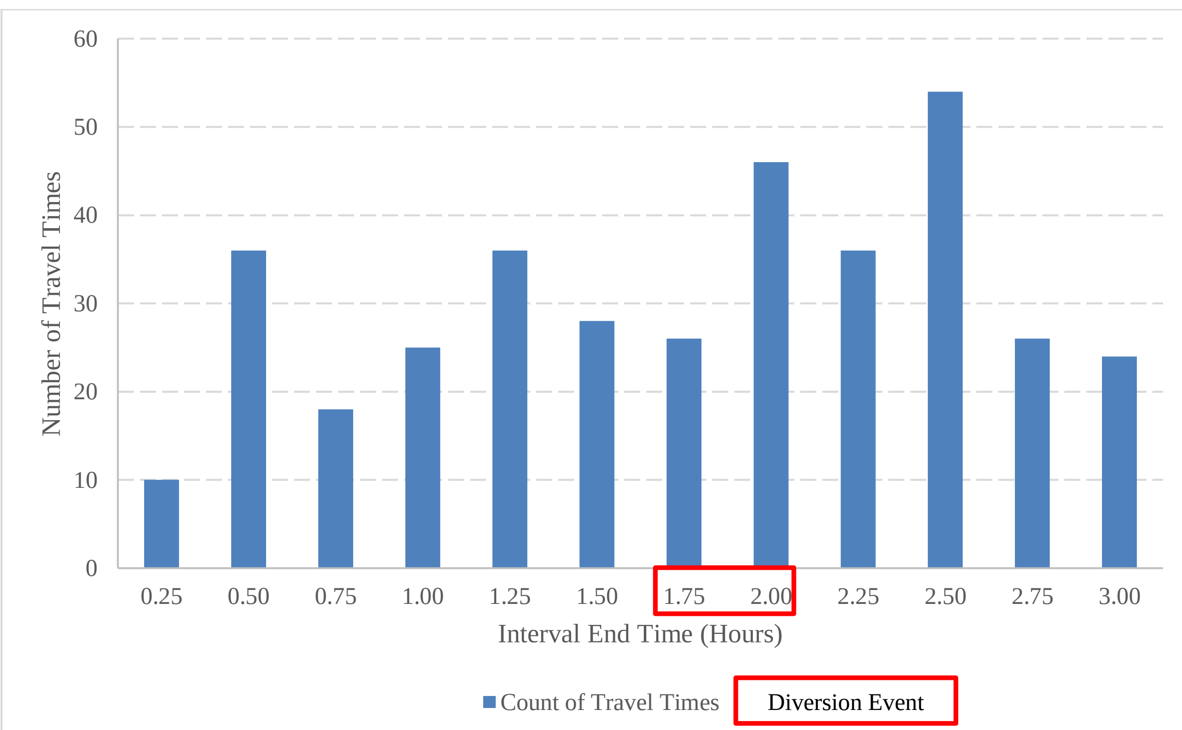

Figure C-3 (b) – Diversion Scenario 4 count of travel times by interval end

Figure C-4 (a) – Diversion Scenario 5 travel times vs historical data set

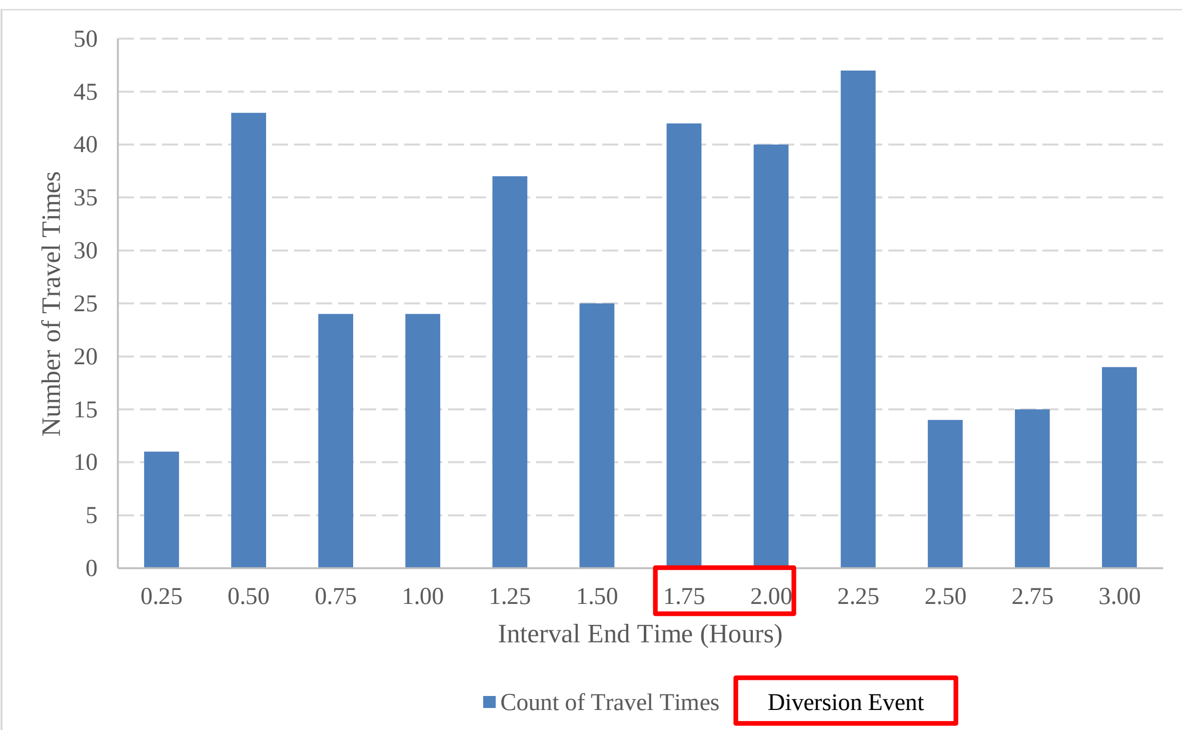

Figure C-4 (b) – Diversion Scenario 5 count of travel times by interval end

Figure C-5 (a) – Diversion Scenario 6 travel times vs historical data set

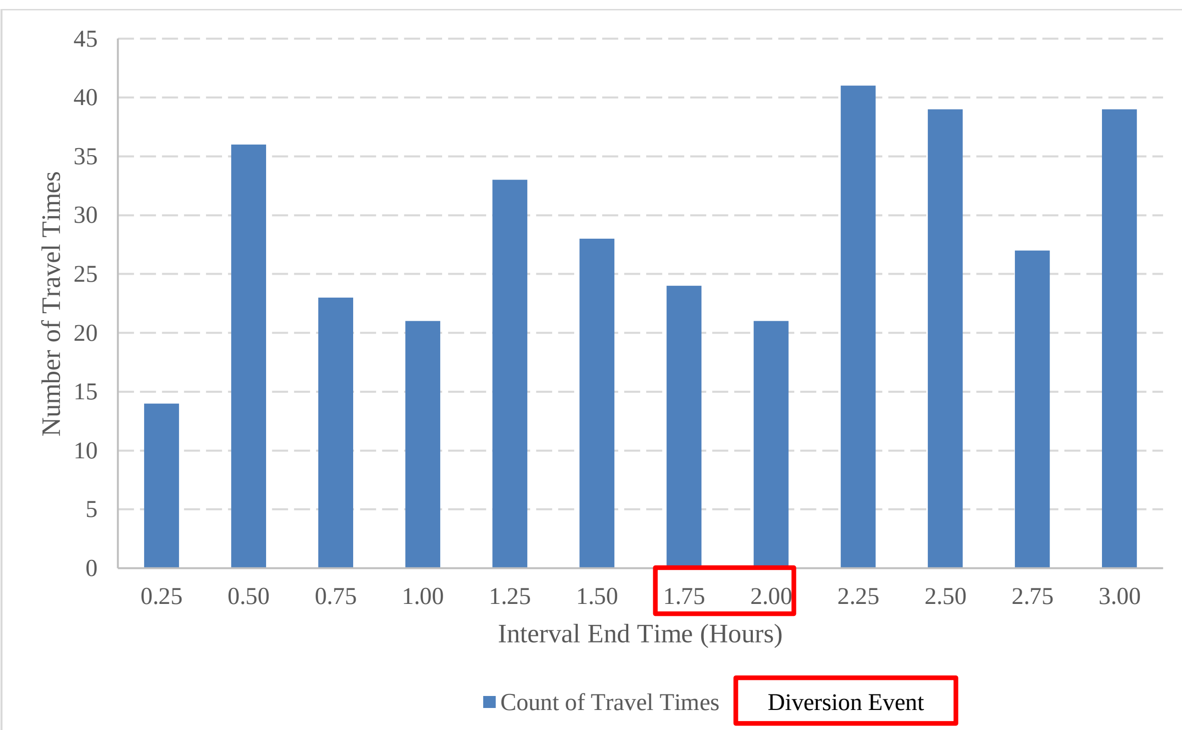

Figure C-5 (b) – Diversion Scenario 6 count of travel times by interval end