

# **Adaptive Traffic Signal Optimization Using Bluetooth Data**

by

Amir Zarinbal Masouleh

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## **Examining Committee Membership**

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner

NAME: Dr. Hesham Rakha

Title: Professor, Virginia Tech

Supervisor(s)

NAME: Dr. Bruce Hellinga

Title: Professor, University of Waterloo

Internal Member

NAME: Dr. Liping Fu

Title: Professor, University of Waterloo

Internal Member

NAME: Dr. Jeff Casello

Title: Professor, University of Waterloo

Internal-external Member

NAME: Dr. John Zelek

Title: Associate Professor, University of Waterloo

## **Author's Declaration**

I hereby declare that I am the sole author of this 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.

## **Abstract**

Traffic congestion continues to increase in urban centers causing significant economic, environmental, and social impacts. However, as urban areas become more densely developed, opportunities to build more roadways decline and there is an increased emphasis to maximize the utilization of the existing facilities through the use of more effective advanced traffic management systems (ATMS).

In recent years, Bluetooth technology has been adapted for use as a sensor for measuring vehicle travel times along a segment of roadway. However, using Bluetooth technology in ATMS such as advanced traffic signal controls has been limited in part because there has been little research conducted to investigate the opportunity to estimate intersection control delay and desired travel time using Bluetooth collected data. Furthermore, until recently, there has been a lack of tools, such as simulation, to predict the behavior of the system before it is developed and deployed. Therefore, the main intention of this research was to develop a robust framework for adaptive traffic signal control using Bluetooth detectors as the main source of data.

In this thesis, I addressed the aforementioned challenges and proposed the first integrated framework for real time adaptive traffic signal management using Bluetooth data through the following steps:

1. I have developed a state of the art simulation framework to simulate the Bluetooth detection process. The simulation model was calibrated and validated using field data collected from two custom built Bluetooth detectors. The proposed simulation framework was combined with commercially available traffic microsimulation models to evaluate and develop the use of Bluetooth technology within ATMS.
2. I proposed two methods for estimating control delay at signalized intersections using Bluetooth technology. Method 1 requires data from a single Bluetooth detector deployed at the intersection and estimates delay on the basis of the measured Bluetooth dwell time. This model has a high level of accuracy when the queue length is less than the effective range of the Bluetooth detectors but performs poorly when queues exceed the detector range. Method 2 uses Bluetooth measured travel time to estimate control

delay. This method requires data from two Bluetooth detectors, one at the intersection and one upstream. This method can be used regardless of the length of queues. The methods were evaluated using a custom-built simulation framework and field data. The results show that the proposed methods provide an accuracy of mean absolute error equal to 3 seconds, indicating that they are suitable for estimating control delay at signalized intersections.

3. I proposed a method to dynamically optimize green splits of signalized intersection on the basis of control delay estimated from Bluetooth detector data. Evaluation of the proposed method using a simulated hypothetical intersection demonstrated that proposed method is able to provide reduction in average delay in comparison with fixed signal timing and fully actuated controller.
4. I proposed and evaluated a method to estimate the desired travel time<sup>1</sup> of the platoon in real-time and then use this estimate to optimize the offset of signalized intersections in a corridor. The proposed method has been evaluated using simulated data for a range of traffic demands and weather conditions and results indicate that the proposed method can provide up to a 75% reduction in average vehicle delay for vehicles discharging in the coordinated phase in comparison with fixed offset timing in different weather conditions.

*Keywords*— Bluetooth, Simulation, Advanced Traffic Management Systems, Adaptive Traffic Signal Optimization, Green Split Optimization, Offset Optimization, Delay Estimation, Desired Travel Time Estimation;

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<sup>1</sup> Desired travel time is the time required for the platoon to travel from the upstream intersection to the downstream intersection when there is no delay incurred at the downstream intersection

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## **Dedication**

This thesis is dedicated to ambitious researchers all around the world who devoted their lives for the promotion of science.

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# Chapter 1

## Introduction

### 1.1 Background

Traffic congestion continues to increase in urban centres causing significant economic, environmental, and social impacts. These impacts can be measured in terms of delay, excessive fuel consumption, emission of air contaminants, greenhouse gases, costs associated with unreliability of transportation systems, safety, etc. A recent study estimated the annual costs in Canada for some of these impacts; \$5.18 billion in the form of delay, \$0.32 billion for wasted fuel, and \$0.07 billion in extra Green House Gas emissions (in 2002 dollar value). These costs are equal to 0.81% of Canada's GDP (iTRANS 2006).

A wide range of strategies have been considered to address the traffic congestion problem. Historically, the most common approach to tackle congestion was to increase the capacity of the road network through construction of new infrastructures. However, as urban areas become more densely developed, opportunities to build more roadways decline and there is an increased emphasis to maximize the utilization of the existing facilities through the use of more effective system management.

The majority of intersections within the urban environment are at-grade, meaning that the intersection capacity must be shared by conflicting traffic movements. Typically these intersections also constitute the capacity bottlenecks within the road network. Consequently, improving the performance of these signalized intersections is critical for increasing the utilization of the available roadway capacity and improving the overall performance of the urban traffic network.

Intersection performance is usually quantified in terms of average vehicle delay and queue length. Average vehicle delay can be determined for a single lane, a lane group, an approach or the intersection as a whole. When aggregating the delays across multiple lanes, it is typical to compute the volume weighted average delay to account for differences in the number of vehicles using different lanes to make their turning manoeuvres. The level of service (LOS) is



a qualitative measure of traffic flow expressed based on the average vehicle delay of an intersection. The objective of the traffic signal timing design process, as embodied within the Canadian Capacity Guide (CCG) (2008) and the Highway Capacity Manual (HCM) (2010), is to minimize the delay and achieve better LOS. As a result, intersection delay is the most significant input parameter for design and optimization of traffic signal timing and evaluation of traffic operations at signalized intersections.

## 1.2 Signalized Intersection Operations

The travel times that vehicles experience as they traverse an arterial can be decomposed into two parts, namely (1) free flow travel times; and (2) delays. In general, delays may occur at the intersection as a result of the intersection control, or mid-link as a result of interference from turning vehicles from cross streets, bus maneuvers at bus stops, vehicles engaged in parking maneuvers when on-street parking is permitted, crossing pedestrians and cyclists, commercial vehicles making deliveries, etc.

The impact of traffic signal operations on vehicles delay is illustrated in Figure 1-1. Vehicle A arrives at the intersection when the traffic signal is green and therefore is able to proceed through the intersection without any delay. On the contrary, vehicle B, which is traveling at the same speed as vehicle A, arrives at the intersection just after the signal turns red. As a result vehicle B decelerates, and stops at the intersection. After the signal turns green again, vehicle B starts to accelerate, and reaches the desired cruising speed. As illustrated in Figure 1-1, the control delay that a vehicle (e.g. vehicle B) experiences ( $D_B$ ) is expressed as:

$$D_B = d_d + d_s + d_a \quad (1-1)$$

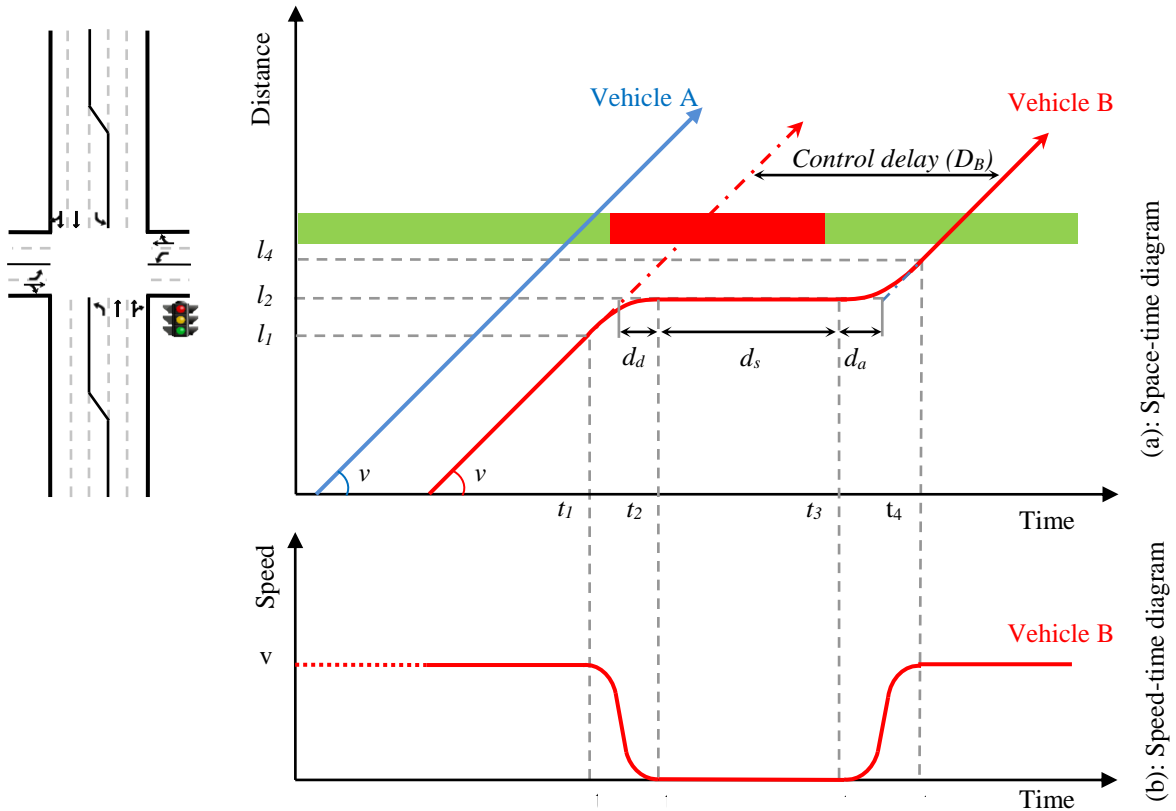
$$d_d = t_2 - t_1 - \frac{l_2 - l_1}{v} \quad (1-2)$$

$$d_s = t_3 - t_2 \quad (1-3)$$

$$d_a = t_4 - t_3 - \frac{l_4 - l_2}{v} \quad (1-4)$$

$$\Rightarrow D_B = t_4 - t_1 - \frac{l_4 - l_1}{v} \quad (1-5)$$

Where,  $D_B$  is control delay,  $d_d$  is deceleration delay,  $d_s$  is stopped delay,  $d_a$  is acceleration delay,  $v$  is the free-flow speed of the vehicle, and  $l_1$ ,  $l_2$ , and  $l_4$  are the locations where the vehicle starts to decelerate, stop, and reaches the same free-flow speed.



**Figure 1-1: The effect of signal control and arrival time on intersection delay**

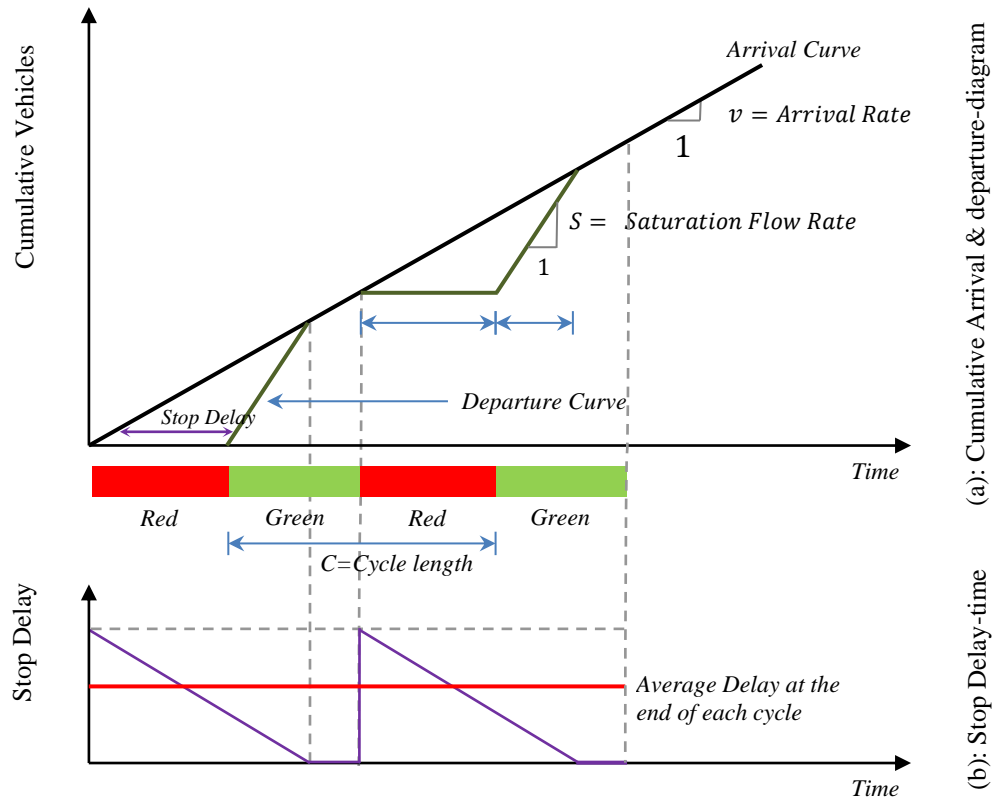
When demand is less than capacity, then all vehicles arriving during a single cycle are able to clear the intersection during the green interval. In this situation the approach is considered to be under-saturated. When demand exceeds capacity, the approach is considered to be over-saturated.

For under-saturated conditions the stop delay may vary between a maximum value equal to the duration of the red interval ( $r$ ) and a minimum of zero. If we assume deterministic uniform arrival and service<sup>1</sup> rates, and we treat the signal as a pulse queue (i.e. vertical queues), then we ignore the acceleration and deceleration delays (i.e. we consider only the stopped delay),

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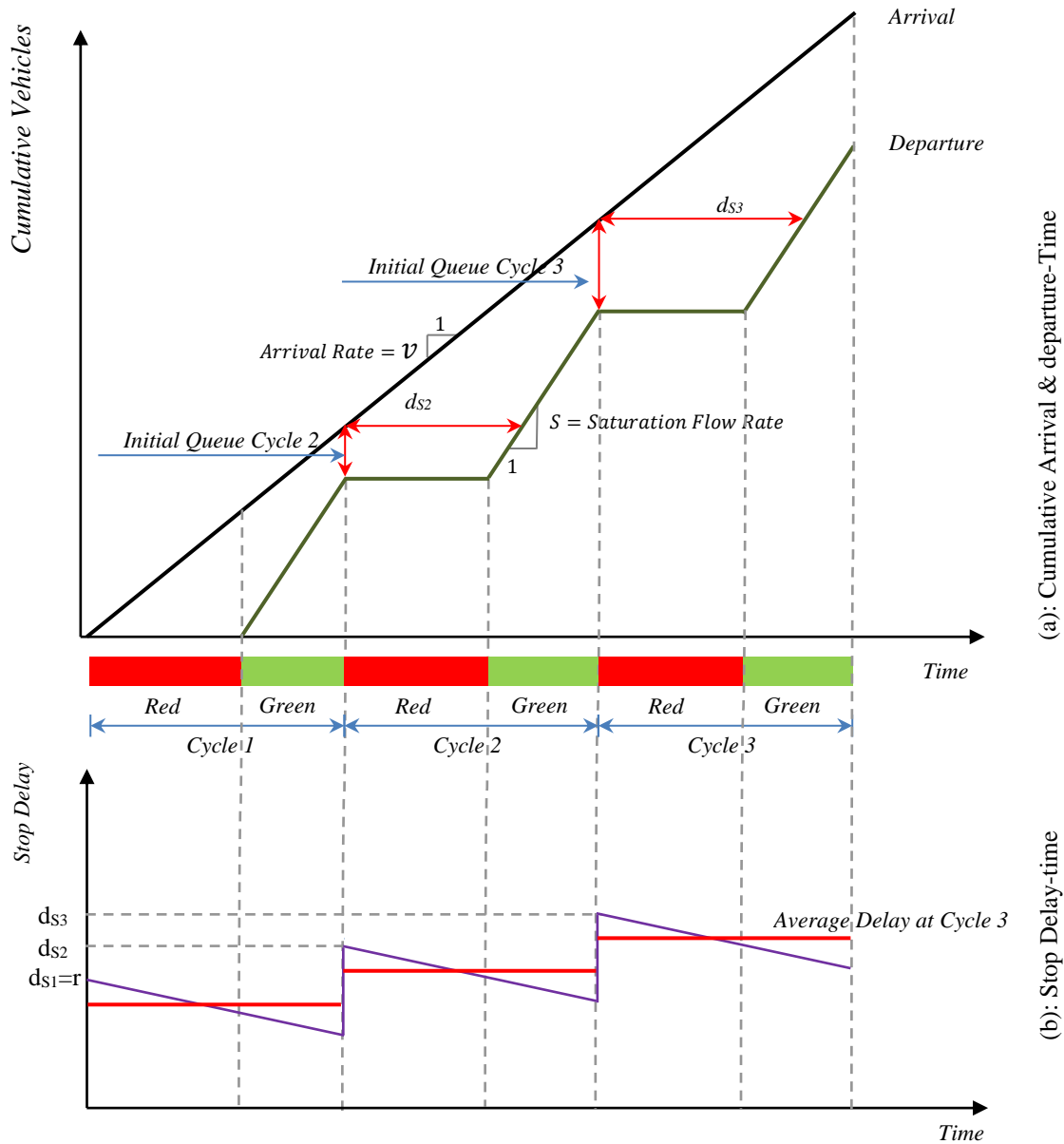
<sup>1</sup> Service rate is also referred to as the saturation flow rate

and vehicle stop delay is a deterministic function of the vehicle arrival time (relative to the signal timing) and the signal timing plan as illustrated in Figure 1-2. This type of delay is referred to as uniform delay.



**Figure 1-2: Stop delay variation due to arrival time and signal control characteristics- Deterministic under-saturated Conditions**

However, if the demand is greater than the available capacity (over-saturated conditions) as illustrated in Figure 1-3, the experienced delay will also be affected by the existing queue at the beginning of the red interval of each cycle (e.g.  $d_{s2}$ ,  $d_{s3}$ ). The delay variation for oversaturated conditions (assuming deterministic arrival and service times) is depicted in Figure 1-3.



**Figure 1-3: Stop delay variation due to arrival time and signal control characteristics  
Deterministic Oversaturated Conditions**

### 1.3 Traffic Signal Control Systems

Traffic signal control systems can be classified as:

1. Fixed time
2. Actuated

3. Responsive
4. Adaptive

Fixed time signal control systems implement signal timing plans that are calculated off-line (on the basis of historical data) and implemented as a function of the time of day (e.g. AM peak from 7:30 – 10 AM) and day of week (e.g. weekday versus weekend). The signal control system does not have any information about the actual traffic conditions on the network and therefore when incidents, planned events (e.g., construction, football game, etc.), extreme weather events, or other unusual conditions cause the traffic conditions to be substantially different from the “typical” conditions, the timing plan implemented is often not the one best suited to current conditions.

Actuated traffic signal control systems<sup>1</sup> are similar to fixed-time systems, in that they implement time of day plans. However, these systems include dedicated traffic sensors (e.g. loop detectors) on one or more of the intersection approaches. These sensors are typically located near the stop line and are used to determine if a vehicle is waiting to make a specific movement (e.g. a left turn). If a vehicle is detected, then the signal control system may switch to a specific phase (e.g. a protected left turn phase) or may extend the green interval for that phase. Actuated signal control systems have better performance than fixed time systems because they can avoid allocating capacity to the movements with no demand. However, these systems also have several limitations, namely:

1. They are more expensive to install and operate as they require the deployment of dedicated traffic sensors;
2. The intersection is treated as an isolated element in the network. The possible effects on downstream intersections resulting from changes made to the signal timings at the current intersection are ignored.
3. The signal control only reacts to actuations after vehicles arrive at the sensors. Since sensors are typically deployed at the stop line, this implies that vehicles will need to

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<sup>1</sup> Actuated control systems enable actuation on all approaches; Semi-actuated systems enable actuation on just a sub-set of the approaches (typically just the minor street approaches) or just certain turning movements (typically left turns).

arrive at the stop line and come to a stop before the signal will be able to react. There is no attempt to detect vehicles upstream of the intersection and predict downstream future demands so that the signal timing can be altered before vehicles arrive at the intersection.

4. Actuated signal control systems are not able to change the offset, which controls the level of coordination between the current intersection and upstream or downstream intersections (i.e. offset has a key influence on the progression factor,  $k_f$ , in the delay equations).

The most common traffic sensor for actuated control is the induction loop detector. Loop detectors consist of a copper wire embedded within the road pavement. When a vehicle passes over the loop, a current is induced and this signal is measured and sent to the signal controller. The signal control system then knows that a vehicle is present.

Traffic responsive control systems are those which use information from traffic sensors to determine if it is advantageous to switch from the existing signal timing plan to some other, pre-defined, signal timing plan. A library of plans is developed and the selection of the optimal plan for the current conditions is done in real-time.

Adaptive traffic control systems are more sophisticated than actuated control systems as they attempt to address the limitations of actuated control systems by combining real-time traffic conditions monitoring with optimization of signal timings (Figure 1-5).

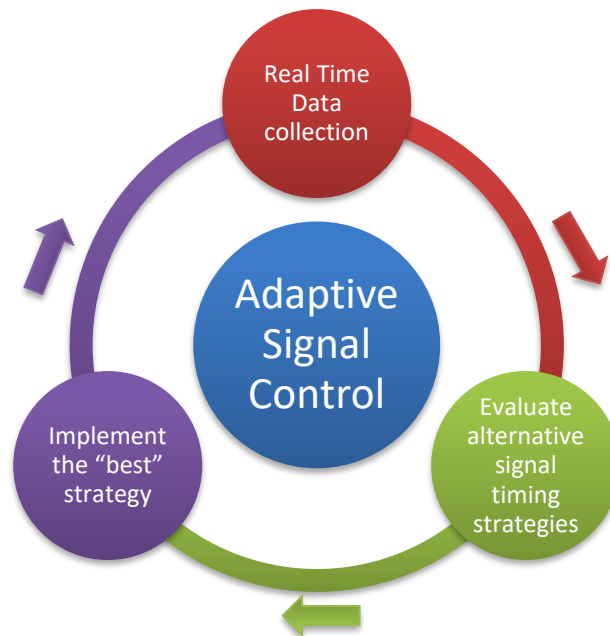
Adaptive control systems typically provide the following capabilities:

1. A network of dedicated traffic sensors is used to detect traffic volumes on each approach and near-future traffic demands are estimated on the basis of these measurements.
2. Intersections are considered as part of a corridor and therefore the interaction between each intersection and its upstream and downstream intersections is considered.
3. All aspects of the signal timing plan are considered within the optimization and consequently, signal timing changes may consist of dropping or inserting a phase;

increasing or decreasing the green interval duration; changing the cycle length; and/or changing the offset.

However, these systems also suffer from the following limitations:

1. Require a larger number of dedicated traffic sensors (most commonly loop detectors) which increases the required initial investment and ongoing maintenance costs. Typically, loop detectors must be installed at both the stop line and the upstream end of the approach link.
2. Loop detectors do not provide the capability of measuring vehicle travel times along the arterial link. Consequently, most existing systems use an assumed constant platoon speed (or travel time) for determining coordination. However, if actual travel times deviate from the assumed value (e.g. during inclement weather), the system is unable to provide optimal coordination.



**Figure 1-4 Framework of Adaptive Traffic Signal Controllers**

#### **1.4 Problem Statement**

One of the main problems with existing adaptive signal control systems is the cost of the deployment, operations, and maintenance of the large number of dedicated traffic sensors. On the other hand, most existing actuated signal control systems are not able to optimize

coordination in response to changing traffic or environmental conditions. There appears to be an opportunity to develop a signal control system that is more efficient than actuated control and more cost effective than traditional adaptive control systems. The goal of this research is to develop and evaluate methods for making use of Bluetooth detector data for dynamically improving the operation of signalized intersections, specifically by dynamically adjusting the allocation of green times to different phases and by dynamically adjusting offsets to improve coordination.

## **1.5 Bluetooth Detectors**

Actuated traffic signal control systems are a cost effective approach for optimizing isolated intersection traffic signal operation; however their inability to address signal coordination along urban arterials may result in inefficient allocation of capacity (i.e. green time). In addition when adverse weather and/or incidents such as collisions occur that affect the saturation flow rate or the travel time between consecutive intersections, actuated traffic control systems cannot measure these changes and therefore, provide sub-optimal signal timings.

Adaptive traffic signal control systems are able to measure and respond to changing traffic patterns. However, in addition to being more costly, they are not able to measure and incorporate changes in link travel time which is the basic input parameter for signal coordination optimization.

To improve the performance of actuated and/or adaptive traffic signal control systems, there is a need to devise a cost-effective method which is able to measure intersection delay and link travel times in real-time and incorporate these data into an optimization procedure to dynamically adjust signal timing plans to minimize delay on urban arterials.

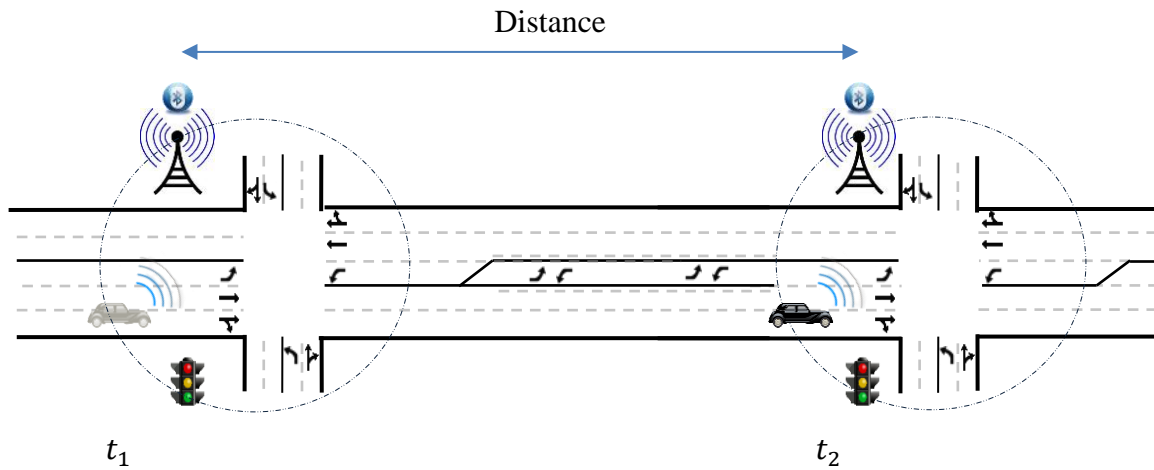
The recent developments in Bluetooth detection technology provide such an opportunity. Bluetooth is a wireless communication standard that has been adopted in many consumer electronic products (e.g. cell phones) to enable direct wireless communications between paired devices.

In order to identify possible devices, Bluetooth transceivers continuously transmit their unique 48 bit ID (address) known as Media Access Code (MAC). Each Bluetooth detector



continuously performs inquiry scans in specific radio frequencies. The Bluetooth devices which are in discovery mode may be detected while they are passing the detection zone<sup>1</sup> of the detector even when they are already engaged in communication with another device. The detector records the MAC and the time of detection of Bluetooth devices. I refer to each record (i.e. MAC address and time of detection) as a “hit”. Each unique Bluetooth device can be detected several times during the time it takes to pass the detection zone (and there we will obtain multiple hits for this device).

In recent years, Bluetooth detectors have been widely considered as an efficient and straightforward tool for measuring travel time and average travel speed both on freeways and arterials (Barceló et al. 2010, Quayle et al. 2010, Moghaddam, Hellinga 2013, Díaz, González & Wilby 2016). Travel time is calculated by the time difference of the matched MAC at successive detectors and average speed is computed on the basis of the travel time and the distance between the successive stations (Figure 1-5).



**Figure 1-5 Travel time measurement using Bluetooth scanners**

In addition to these data it is possible to extract additional information from Bluetooth detections. The time stamp of the hits for each Bluetooth device as well as the number of hits provide additional information regarding the dwell time (e.g. the difference between the time

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<sup>1</sup> The radius of this detection is on the order of 100m for Class 1 Bluetooth devices.

stamps of the first and last hits for a Bluetooth device that traversed the detection zone) and the experienced delay for different movements in intersections.

The main advantages of using Bluetooth scanners are:

- Travel time can be measured.
- The detection process can be done anonymously.
- The technique does not violate privacy as there is no way to correlate a MAC address with a specific vehicle or with a specific person.
- It reduces the data gathering costs.

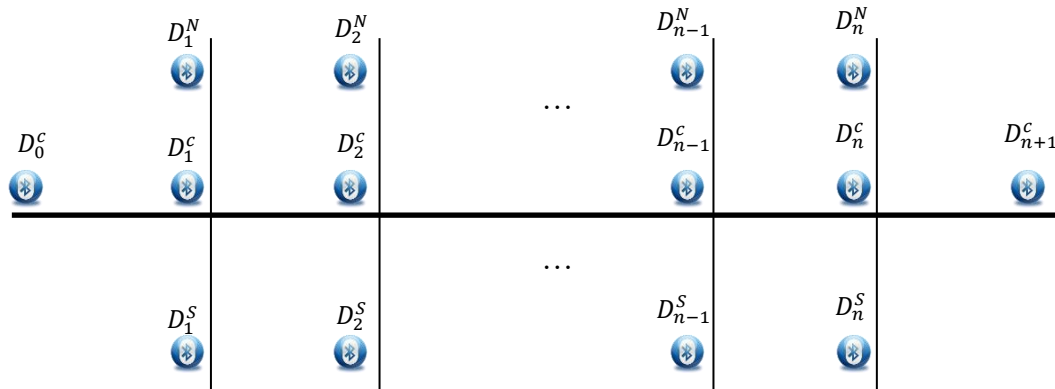
However, the accuracy of Bluetooth data is impacted by the following sources of errors:

- A single vehicle may be carrying multiple Bluetooth devices that may result in sampling bias.
- Detected Bluetooth devices may not always be in personal vehicles. Bluetooth devices may be carried by other motorized vehicles such as taxies, buses, and emergency vehicles, or be associated with non-motorized modes (e.g. cyclists or pedestrians). The travel times and other data obtained from these other sources may not accurately represent the traffic conditions experienced by the majority of the road users and therefore should be considered as outliers.
- A single Bluetooth detector is unable to detect a vehicle's traveled route or provide any information regarding the turning movement made by vehicles at intersections.
- Bluetooth detectors do not provide any information regarding whether detected vehicles made planned stops along the segment which may result in overestimation of link travel times.
- Bluetooth detectors do not provide any information about the location within the detection zone of the detected devices
- Bluetooth detection data in a single station do not provide any information about travel direction until a secondary detection of the same device occurs at some other Bluetooth detection station. As a result, there is an inherent lag in measuring link travel times using Bluetooth detectors.

### 1.5.1 Configuration of Detectors

Bluetooth detectors typically use omni-directional antennas and therefore they are not able to identify the direction from which Bluetooth radio signals are being transmitted. For these detectors, it is not possible to associate a specific MAC with a given turning movement using only the information collected by a single detector. However, distinguishing delays by turning movement (or equivalently by lane group) is an essential requirement for traffic signal control optimization.

In order to capture the delay associated with different movements at each intersection and travel time of each segment, detectors are required to be installed according to Figure 1-6. In this figure, each line is the representative of a street.



**Figure 1-6: Required configuration of Bluetooth detectors using Omni-directional sensors**

In this configuration, detectors are installed at each intersection in the main corridor ( $D_i^C$ ) as indicated by a thick solid line, and the upstream and downstream intersections of each crossing street ( $D_i^N, D_i^S$ ). By matching the MAC IDs detected at the main corridor with those detected at crossing streets, it is possible to determine the travel times and corresponding delays for each movement including the through movement at the corridor ( $D_i^C \leftrightarrow D_{i+1}^C$ ), through movements at the cross streets ( $D_i^N \leftrightarrow D_i^S$ ), and turning movements ( $D_i^N \leftrightarrow D_{i+1}^C, D_i^N \leftrightarrow D_{i-1}^C, D_i^S \leftrightarrow D_{i+1}^C, D_i^S \leftrightarrow D_{i-1}^C$ ).

As illustrated in Figure 1-6, the number of required sensors is:

$$N_b = 3n + 2 \tag{1-6}$$

Where,  $N_b$  is the number of required Bluetooth detectors and  $n$  is the number of intersections in the corridor.

The consequences of using this detector deployment configuration are:

- 1- In order to capture the direction of the movement of the vehicles in intersections, each vehicle must be detected by 3 successive detectors (i.e. an upstream detector; the detector at the intersection of interest; and a downstream detector). This may result in lower number of successful movement detections.
- 2- This configuration will introduce a time lag in estimation of delay for each movement as it is necessary to wait for 3 successive detections of unique MAC IDs before being able to estimate the delay and travel time for a particular movement.

## **1.6 Research Goals and Objectives**

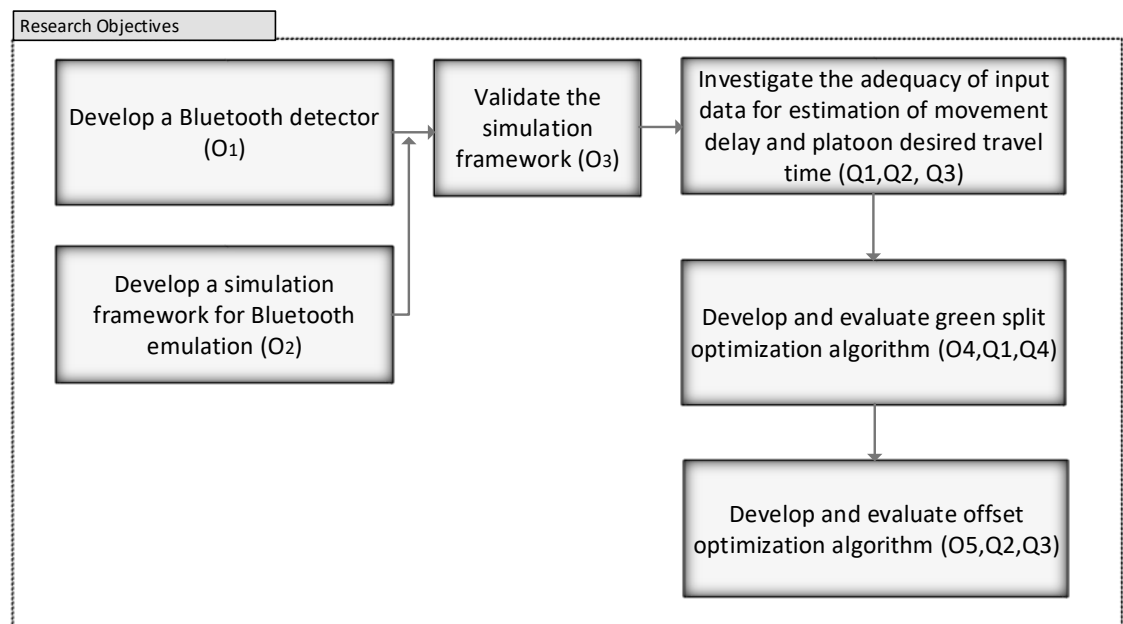
The goal of this research is to improve traffic signal control through incorporation of the data acquired from Bluetooth detectors. Specifically, this research attempts to address the following four research questions:

1. Can data acquired from Bluetooth detectors be used to estimate the existing performance of a signalized intersection (in terms of delays for each lane group) and if so can these estimates be used as an input to the traffic signal optimization process?
2. Can the data acquired from a pair of Bluetooth detectors be used to accurately measure desired travel times for the purpose of real-time traffic signal coordination?
3. Can the estimated desired travel times be used to optimize signal offsets in real-time, and if so, what benefits are achieved and under what conditions?
4. Finally, what are the performance characteristics of a traffic signal control system that relies on Bluetooth acquired data rather than traditional sensor data? How does this performance change as a function of traffic conditions, geometry, and signal timings?

In order to answer these four research questions, we define the following research objectives.

1. Develop a Bluetooth detector prototype along with supporting software so that field data can be collected to support this research.
2. Develop a simulation framework in which a custom-built Bluetooth emulation module is incorporated within the Vissim traffic simulation model so that simulation experiments can be conducted to emulate the real-world and the simulation model can be used to test signal control algorithms which rely on Bluetooth data.
3. Validate the simulation framework using field data collected using the Bluetooth detector developed as part of Objective 1.
4. Develop an algorithm for optimizing green split of signal timings that relies on data acquired from Bluetooth detectors. Evaluate the algorithm using the simulation framework developed as part of Objective 2.
5. Develop an algorithm for optimizing offset of signalized intersection that relies on data acquired from Bluetooth detectors. Evaluate the algorithm using the simulation framework developed as part of Objective 2.

Figure 1-7 shows schematic representation of the research objectives.



**Figure 1-7: Schematic representation of the research objectives**

## **1.7 Thesis Outline**

The remainder of this document is organized as follows.

Chapter 2 describes (i) the developed Bluetooth detector; (ii) the proposed Bluetooth detector simulation framework; and (iii) the evaluation of the proposed simulation framework using collected field data;

Chapter 3 describes the proposed models for estimating control delay and the evaluation of the proposed methods.

Chapter 4 discusses (i) the proposed method for adaptive optimization of green split of signalized intersections using Bluetooth detectors; (ii) calibration of optimization parameters; and (iii) evaluation of the proposed algorithm in various traffic conditions.

Chapter 5 describes (i) the proposed method for estimation of desired travel time of platoon; (ii) the adaptive offset optimization of signalized intersections using Bluetooth technology (iii) calibration of optimization parameters; and (iv) evaluation of the proposed algorithm in different weather conditions.

Chapter 6 summarizes the research conclusions and contributions of this thesis and provides the recommendations for further studies.

## **Chapter 2**

# **Simulation of Bluetooth Inquiry Process for Application in Transportation Engineering<sup>1</sup>**

### **2.1 Introduction**

Bluetooth is a wireless communication standard that has been adopted in many consumer electronic products (e.g. cell phones) to enable direct wireless communications between paired devices.

In order to identify possible devices, each Bluetooth detector continuously performs inquiry scans in a specific set of radio frequencies. The Bluetooth devices (slaves) which are in discovery mode may be detected while they are present within the detection zone of the detector even when they are already engaged in communication with another device. These potential slaves transmit their unique 48-bit ID (address) known as Media Access Code (MAC) once they receive the inquiry scan packet. The detector records the MAC and the time of detection of the Bluetooth device. We refer to each record (i.e. MAC address and time of detection) as a “hit”. If a device remains within the detection zone for a sufficient period of time, then the device can be detected several times and therefore the detector obtains multiple hits for this device. We refer to each set of hit records for each unique device as a “detection”.

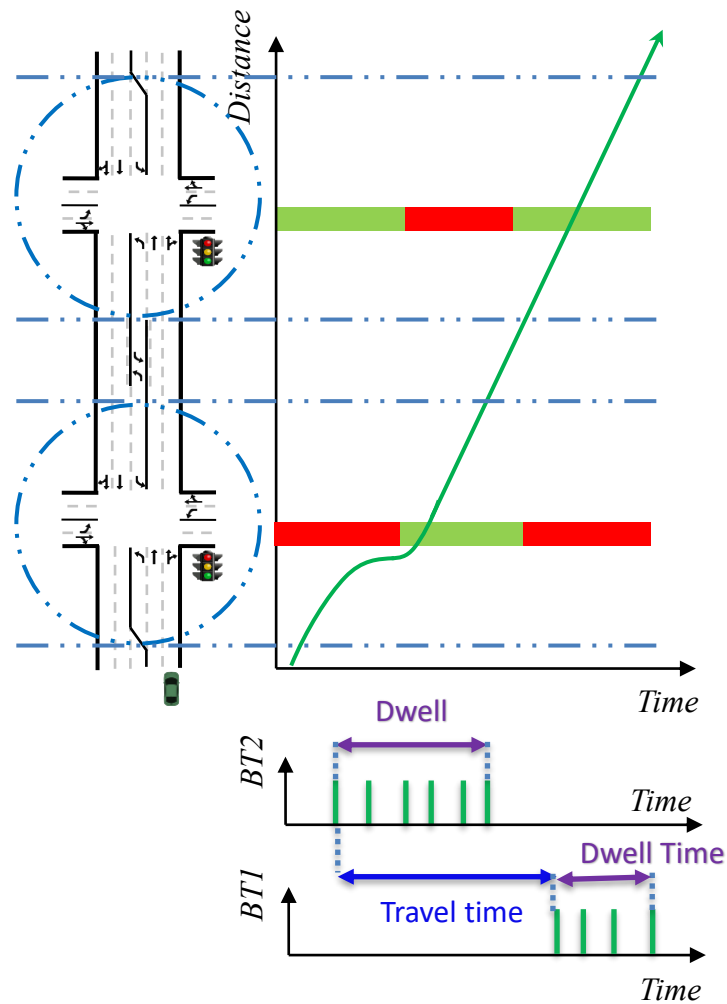
In recent years, Bluetooth detectors have gained increasing attention as an efficient technology for measuring travel time and average travel speed on freeways and arterials. Travel time is calculated by the time difference of the matched MAC at successive detectors and

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<sup>1</sup> This is a submitted manuscript of an article submitted to IEEE Transactions on Intelligent Transportation Systems on December 2016 by Amir Zarinbal Masouleh and Bruce Hellinga, “Simulation of Bluetooth Inquiry Process for Application in Transportation Engineering”

average speed is computed on the basis of the travel time and the distance between the successive detector stations (Figure 2-1).

However, it is possible to extract additional information from Bluetooth detections. The time stamp of the hits for each Bluetooth device as well as the number of hits provide additional information regarding the dwell time (e.g. the difference between the time stamps of the first and last hits for a Bluetooth device that traversed the detection zone) and the experienced delay for different movements in intersections.



**Figure 2-1: Application of Bluetooth detectors in transportation engineering**

To-date most of these Bluetooth detector systems have been used for acquiring data for Advanced Traveler Information Systems (ATIS) and for evaluation of traffic management



strategies. However, there is a potential to use this information in Advanced Traffic Management Systems (ATMS) such as real time traffic signal optimization. In order to develop these management systems, there is a need to have an accurate and efficient simulation model that can be used as a test bed in development, optimization, and evaluation of these systems prior to system construction and deployment.

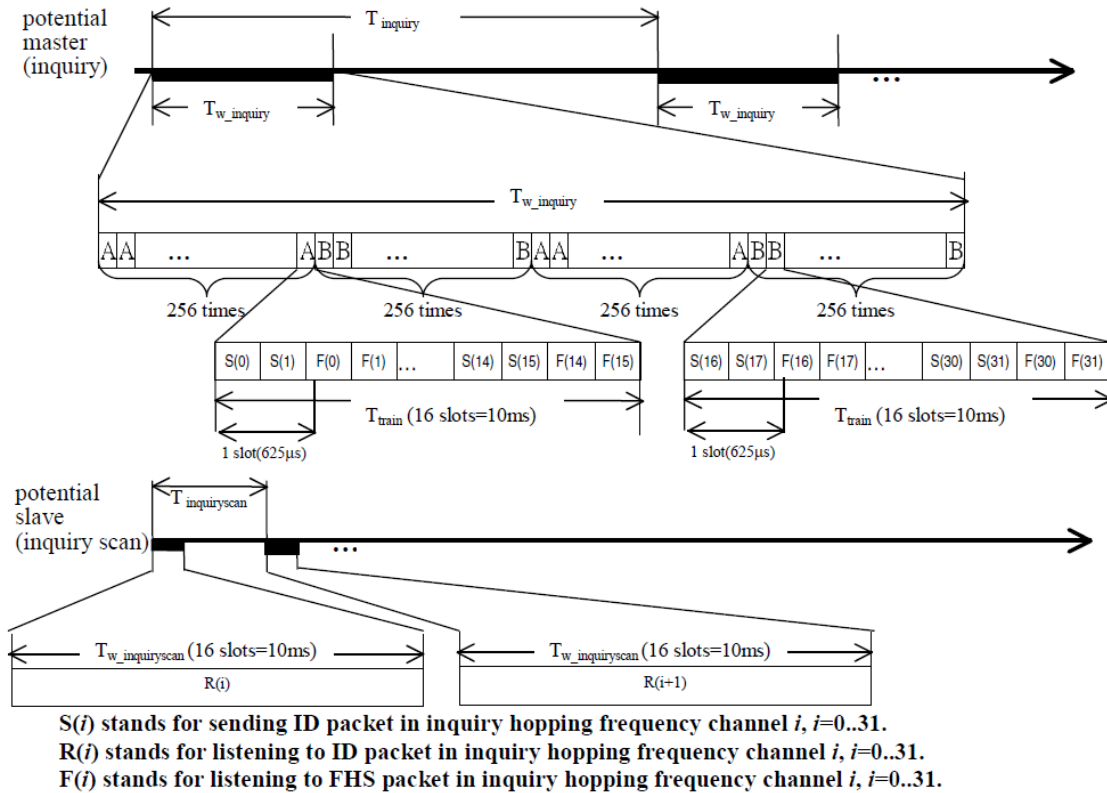
## 2.2 Bluetooth Inquiry Process

In Bluetooth technology the frequency that devices communicate with each other changes with time (Frequency Hopping Spread Spectrum). The sequence of channels which each device listens on is changed based on its clock. In order to create a network, it is required that these clocks be synchronized.

In this type of network, a device is assigned as *Master* to coordinate the communication between devices (*Slaves*). In the Bluetooth literature, the detector acts as the Master device or the *Inquirer* and the Bluetooth devices which should be detected are the Slaves or *Inquiry Scanner*. This network is called a “Piconet” network. Figure 2-2 shows the inquiry process in the Bluetooth protocol. Every  $T_{\text{inquiry}}$  seconds the Master performs a search for other devices during  $T_{\text{w\_inquiry}}$  seconds (this search is called an *inquiry*). The Bluetooth wireless spectrum is divided into 32 different channels (each having a different frequency spectrum). These 32 channels are divided into two mutually exclusive sets of 16 channels each and are called *train A* and *train B*. The Master scans each channel for  $625 \mu\text{s}$  before moving to the next channel in the train. Thus to perform a single scan of all of the 16 channels in a train requires  $10 \text{ ms}$  ( $T_{\text{train}} = 16 \times 0.625 = 10 \text{ ms}$ ). In each inquiry the Master scans a train 256 times before moving to the other train and consequently it requires  $256 \times 10 \text{ ms} = 2.56 \text{ seconds}$  per train ( $T_{\text{w\_train}} = 2.56 \text{ s}$ ).

The Slave sequentially hops on the 32 channels, but at a much slower speed (called *inquiry scan*). The slave listens to a single, randomly selected, channel for  $T_{\text{w\_inquiryscan}}$  seconds and repeats this process every  $T_{\text{inquiryscan}}$  seconds. It is necessary that  $T_{\text{w\_inquiryscan}} > (T_{\text{train}} = 10\text{ms})$ . Consequently, if the channel selected by the Slave is among the 16 channels of the Master’s selected train then the Slave definitely has the opportunity to receive the inquiry

packet from the Master. Usually Bluetooth systems use  $T_{w\_inquiryscan} = 11.25\text{ ms}$  which is 2 slots ( $2 \times 625\ \mu\text{s}$ ) more than  $T_{train}$ .



**Figure 2-2: Bluetooth Inquiry Protocol Process (Jiang, Lin & Tseng 2004)**

In order to avoid collision between two slaves which are listening to the same channel, once the slave receives an inquiry packet from the master it will not response to the inquiry immediately. Instead, it waits a random time (called the random back off time) between 0 and 1024 time slots (0 and  $639.375\text{ms}$ ) and then responds with an inquiry response packet.

The Bluetooth standard requires that the time difference between two consecutive inquiry scan of slaves should be less than or equal to 2.56 seconds ( $T_{inquiryscan} \leq 2.56\text{ s}$ ) and specifies three modes: R0 ( $T_{inquiryscan} = 0$ ), R1 ( $T_{inquiryscan} \leq 1.28\text{s}$ ) and R2 ( $T_{inquiryscan} \leq 2.56\text{s}$ ). Selection of modes is normally based on the power management strategy of the device. The default mode is R1, but some mobile devices implement R2 to save power.

The time of inquiry window ( $T_{w\_inquiry}$ ) is determined by master. In order to maximize the chance of detection, the Bluetooth standard recommends scanning each train for two  $T_{w\_train}$  meaning that  $T_{w\_inquiry} = 2 \times 2 \times 2.56 = 10.24s$  (IEEE Standards Association 2005). However, as we demonstrate later in this chapter, current commercial Bluetooth modules used for Bluetooth detectors, typically report discovered slaves only at the first time they received the response packet. So as  $T_{w\_inquiry}$  increases, the average time between two consecutive hits also increases and this in turn increases the dwell time and travel time measurement error. Therefore, it is a common practice to scan each train only for one  $T_{w\_train}$  meaning that  $T_{w\_inquiry} = 2 \times 2.56 = 5.12s$ .

As the Bluetooth detectors are continuously inquiring and do not intend to enter the pairing procedure, the scanning of each train for only one  $T_{w\_train}$  has no practical effect on the chance of detection and the chance of not discovering a slave for inquiry windows of 5.12 is 0.1% (Fresnedo, Iglesia & Escudero 2007).

## 2.3 Detection Range

The range of detection and the effect of distance of the slave from the detector is a function of three parameters:

### 2.3.1 Power of transmitter and sensitivity of receivers

The transmission power of Bluetooth devices is categorized in three different classes (Table 2-1). The typical range values provided in Table 2-1 represent the typical detection range of communication devices within each class under ideal conditions.

**Table 2-1 Classes of Bluetooth Devices (Bluetooth Special Interest Group 2014)**

Power Class	Maximum output power	Typical Range
1	100 mW (20 dBm)	100m
2	2.5 mW (4 dBm)	10m
3	1.0 mW (20 dBm)	1m

The Bluetooth technology in general and specifically the inquiry process is a two-way communication process. Therefore, the detection range of a Bluetooth detector does not depend

only on the transmission power of the detector. It also depends on the transmission power of the slaves. Moreover, the sensitivity of the detector has a significant effect on the probability of detecting the slave. The sensitivity is important as a considerable portion of potential slaves are class 2 devices such as cell phones, wireless headsets, etc. The properties of the Master are selected by the transportation agencies when procuring the Bluetooth detectors. However, different slave devices have different properties and the transportation agency does not control the distribution of these devices in the market. Therefore, we will need a model that can represent different types of devices and a field test to verify the model.

### **2.3.2 Antenna**

The Antenna characterization such as gain and polarization has a significant effect on the range of Bluetooth detection. Gain is a measure that represents the electrical efficiency and directivity of the antenna (Porter et al. 2013). The gain is calculated as the ratio of power produced in specific direction to the power produced by a (hypothetical and ideal) lossless omnidirectional antenna. As the gain of an antenna increases the range of the antenna increases in that direction. However, the transmission and reception range in another direction decreases. In Bluetooth applications, the antenna is normally configured to have a higher gain in the horizontal plane and this will decrease the range in vertical plane. Therefore, the installation height and configuration of the antenna is also important to the performance of the Bluetooth detector.

## **2.4 Literature Review**

Most previous studies associated with the Bluetooth protocol have focused on simulation of first successful inquiry and reduction of pairing time. However, in many applications, including transportation detectors, Bluetooth detectors are designed to stay in the inquiry stage and will continuously perform inquiry scans. These detectors will not proceed to pairing stage and multiple inquiry scans may occur on each device during the time these devices remain in the detection zone of the detector.

The current simulation systems for Bluetooth technology can be classified into the following three categories:

### **2.4.1 Simulation of Bluetooth Network and Data Transmission**

These simulation systems are designed to simulate the transfer of Bluetooth data packets. These simulation systems are primarily used to investigate improving the data transfer rate, security, performance, and packet losses (Parvatham 2002, Zhang, Zhu & Cao 2002, Das et al. 2001, IBM Research 2001, MIT NMS Group 2002). These systems cannot be utilized in the simulation of transportation systems as they are not designed for the inquiry process which is the main application of Bluetooth systems in transportation.

### **2.4.2 Reduce Device Discovery Time of Bluetooth**

The Inquiry process is the first step for pairing devices to create a Bluetooth network. In order to improve user experience and usability of Bluetooth systems many studies have been performed to model the inquiry process and reduce the discovery time of potential slaves (Fresnedo, Iglesia & Escudero 2007, Thamrin, Sahib 2009, Isaksson, Fiedler 2004, Mohrehkesh, Nadeem 2014, Cho et al. 2015). Some studies have tried to mathematically model the chance of successful inquiry while others have tried to simulate the inquiry process in different level of details (Peterson, Baldwin & Kharoufeh 2006, Záruba, Chlamtac 2003, Cho et al. 2014).

The goal of these systems is to optimize different control variables and the implementations of Bluetooth protocol such as random back off time, inquiry scan window etc. to improve (reduce) the discovery time (Fresnedo, Iglesia & Escudero 2007).

These models tend to represent the communication system with a great deal of detail including the communication layer of Bluetooth systems, internal clock of devices, channel selection, etc.

However, these models are typically not suitable for modelling transportation applications for the following reasons:

- These models are designed to simulate the Bluetooth inquiry process until the first successful detection of slaves. They do not simulate the behavior of Bluetooth systems for multiple discovery.

- The high level of detail with which the communication systems is represented imposes a substantive computational load making it impractical to apply for road networks with many vehicles and the need to perform multiple runs.
- These systems normally do not consider the effect of distance on the inquiry process.

### 2.4.3 Simulation Bluetooth Detector in Transportation systems

Existing models of Bluetooth systems applied to transportation applications have mainly focused on travel time studies. In these systems, it is a common practice that the travel time between two Bluetooth detectors is calculated as the difference between the time stamp from the first hit in two consecutive detector locations. Most of the focus of these existing models have been on developing a probabilistic method for time of first hit or determining the chance of a device not being detected (Bakula, Schneider IV & Roth 2011).

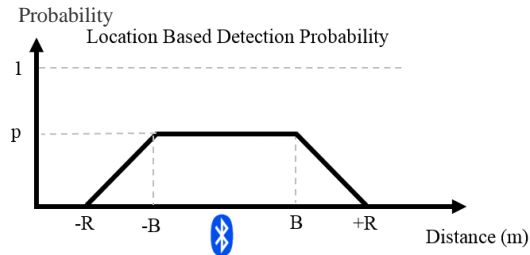
Salek Moghaddam and Hellinga developed a simulation framework for simulation of first hit (Moghaddam, Hellinga 2013) and used the framework to investigate travel time measurement error. In order to consider the effect of distance, their model uses a location based detection probability (Figure 2-3) which they obtained from (Quayle et al. 2010).

This location based detection probability is assumed to have a trapezoidal shape such that if the device is close to the detector (the distance to detector is between 0 and  $B$ ), then the chance of detection is equal to the probability that the channel randomly selected by the slave belongs to train that the Bluetooth detector is currently scanning ( $p$ ). As each train consist of 16 channels out of 32 channels, the value of  $p$  is equal to 0.5.

If the device is located outside the range of the detector ( $R$ ), then probability of detection is zero. When the device is located between  $B$  and  $R$ , then the probability of detection increases linearly from zero to 0.5.

They also assumed that the inquiry scanning process occurred every 1.28 seconds. However, this is the possible scanning interval for the slave. The Master scanning interval (i.e. inquiry window) is typically 5.12 seconds. Moreover, the master and slave have independent internal clocks. Therefore, the hit can happen any time during the Master's scanning interval. Nevertheless, their framework gets the location of Bluetooth enabled vehicles from the traffic

simulation, calculates the distance of each Bluetooth device to each simulated Bluetooth detector, and determines whether or not the vehicle is detected on the basis of the calculated probability of detection at that location. The value of  $R$  was assumed 100m as the detectors are normally a class 1 device. The value  $B$  was assumed as 50m.



**Figure 2-3 Location Based Detection Probability (Moghaddam, Hellinga 2013)**

This model is a reasonable representation for the first detection. However, it may not be sufficiently accurate for applications involving multiple hits such as investigation of Bluetooth dwell time because it does not fully consider the behavior of the master scanning cycle and it assumes that the detection of all devices happens at a constant 1.28 seconds steps of the simulation universal clock. However, each individual device has its own clock and the inquiry response can happen at any time during the scanning interval. Moreover, as discussed earlier in this chapter, even if the device was discovered multiple times during an inquiry, the master device will report the discovered device only at the time of first discovery in that inquiry. Therefore, this model will generate hits that would not happen in reality. As a result, this model is not accurate for the simulation of multiple hits.

#### **2.4.4 Simulation Bluetooth Summary**

To date, most of current Bluetooth simulation frameworks are either focused on reduce device discovery time of Bluetooth devices or they are designed for simulation of Bluetooth networks. The simulation methods for transportation applications do not provide the essential details about the inquiry process. Therefore, in this chapter, we develop an improved Bluetooth simulation model by enhancing the model's representation of the location based probability and the inquiry scanning process.

## 2.5 Improved Location Based Detection Probability

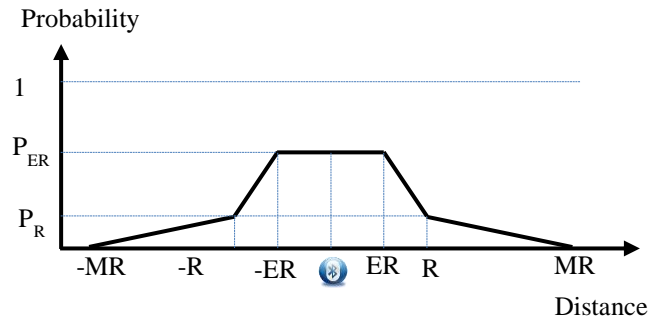
In this chapter, we propose a location based detection probability model (Figure 2-4) which differs from the model proposed by Salek Moghaddam and Hellinga (Figure 2-3) in two ways. First, we define a model that is not restricted to being trapezoidal in shape. More specifically, we represent the probability between the detector's effective range ( $ER$ ) and the maximum range ( $MR$ ) by two linear functions rather than the single linear function in the trapezoidal model. This was done to better represent the actual detection behavior of Bluetooth detectors in the field.

As per Figure 2-4, we define a detection range  $R$ , where  $ER < R < MR$ . Then we can compute the detection probability at any location having distance  $d$  from the detector, as

$$P = \begin{cases} P_{ER}, & d \leq |ER| \\ P_{ER} - \left(\frac{P_{ER}-P_R}{R-ER}\right) |d - ER|, & |ER| < d \leq |R| \\ P_R - \left(\frac{P_R}{MR-R}\right) |d - R|, & |R| < d \leq |MR| \\ 0, & |MR| < d \end{cases} \quad (2-1)$$

Second, we recognize that different types of devices may have different location based detection probabilities and therefore we define a detection probability model for each type of device.

In the field data collection section of this chapter, we describe the calibration of parameters of the proposed model.



**Figure 2-4 Proposed Location Based Detection Probability**



## 2.6 Simulation of Bluetooth Inquiry

The goal of this chapter is to develop a robust simulation framework that is able to simulate the detection of Bluetooth enabled vehicles in transportation applications. Therefore, we need to model two components and their interactions, namely Bluetooth detectors and Bluetooth devices in vehicles. More specifically, we need to model the Bluetooth protocol (just the inquiry stage) and a model to represent the effect of distance and moving vehicles.

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. The trajectories can be obtained from two sources: (1) a GPS logger; or (2) the output from a traffic micro-simulation software. In this research we use the GPS trajectories from field data collection for calibration and verification of the proposed model and the Vissim micro-simulation is used to simulate vehicles passing through a road network and the vehicle trajectories are extracted from the simulation.

The Bluetooth detector (master) object has three major properties:

1.  $T_{w\_inquiry}$  = Duration of the inquiry window during which the master is inquiring for potential Bluetooth devices (e.g. 5.12s).
2. Offset = A random number in the range of  $[0, T_{w\_inquiry})$  that represents the offset time of the start of the inquiry process by the master and the effect of its internal clock.
3. Coordinate (X, Y) which could be the actual GPS longitude and latitude of detector or the coordinate of detector in simulation software.

The traffic simulator records trajectories for all vehicles in the network. However, the level of market penetration (LMP) of discoverable Bluetooth devices in vehicles is less than 100% consequently, a subset of vehicles from the simulation output is randomly marked as Bluetooth enabled vehicles in proportion to the LMP.

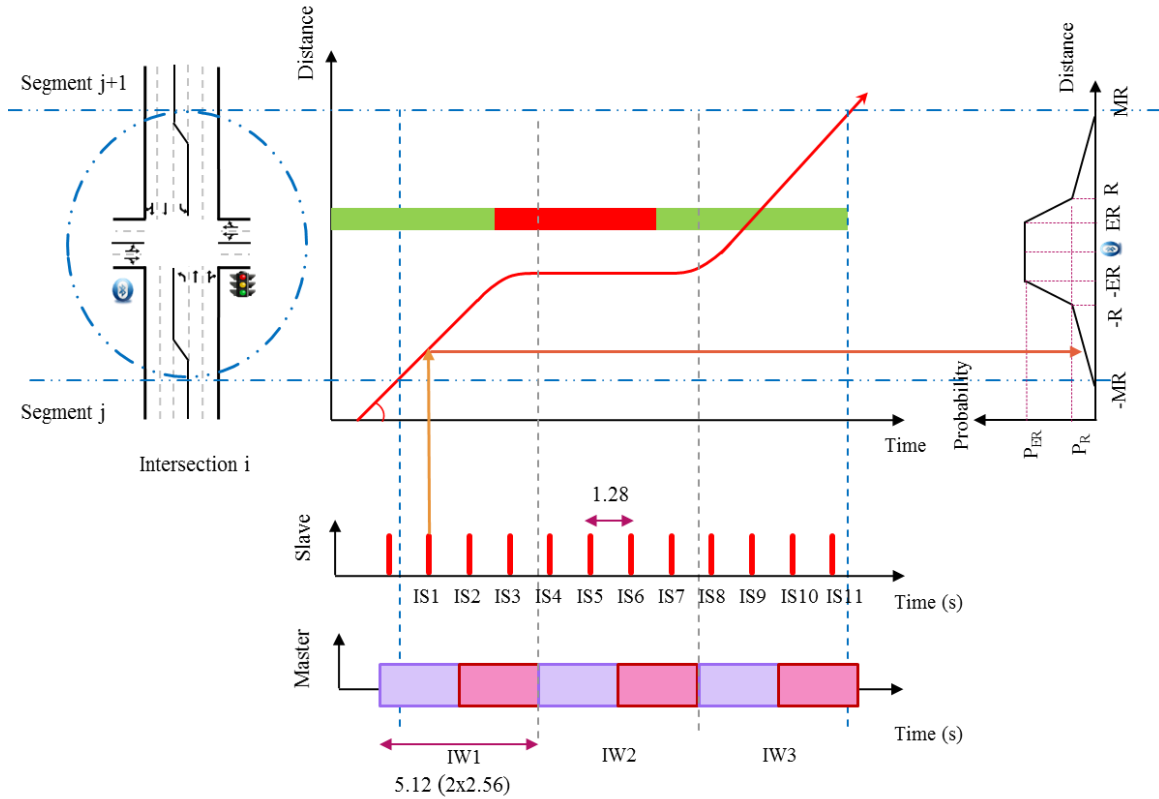
In this simulation each Bluetooth vehicle has four major properties:

1.  $T_{w\_inquiryscan}$  = the time interval at which the Bluetooth vehicle will perform an inquiry scan as a slave (e.g. 1.28 or 2.56).

2. The random offset for the clock of slave which is in the range of  $[0, T_{w\_inquiryscan})$ .
3. Location Based Detection Probability Function. Each Bluetooth device is assigned randomly one of the predefined functions.
4. Position (X,Y) at the time of inquiry scan.

Figure 2-5 illustrates a sample trajectory of a Bluetooth enabled vehicle (slave) in a time space diagram. The timing of the master's inquiry scans and the slave's inquiry scans are shown below the time-space diagram. When the vehicle enters the detection zone of a detector ( $d \leq MR$ ), the first possible hit would be the time of the first inquiry scan of the device in the vehicle (IS1). The location of the vehicle at this time of inquiry is extracted from the traffic simulation model and the distance to the detector ( $d$ ) is calculated. The probability of detection (P) is obtained from the location-based probability model for the type of device in this vehicle, and the detection outcome (i.e. device is detected or not) is the result of the stochastic process.

If the device is detected at IS1, a random back off is added to the detection time and the MAC and time is recorded. The time of the next possible hit is the time of the next inquiry scan of the slave after the end time of the current inquiry window of the master (IW1). In Figure 2-5, this is IS4.



**Figure 2-5: Simulation of inquiry process**

If the device is not detected at IS1, the time of the next possible hit is IS2. This process continues until the time that the vehicle exits the detection zone of the detector.

As a result, the location and time of each hit for the vehicles are recorded in the output database. In order to verify the simulation, we also record the times at which each vehicle entered the detection zone of each detector, passes the sensor, and exited the detection zone. Moreover, the location and time of the first and last Bluetooth hit are recorded.

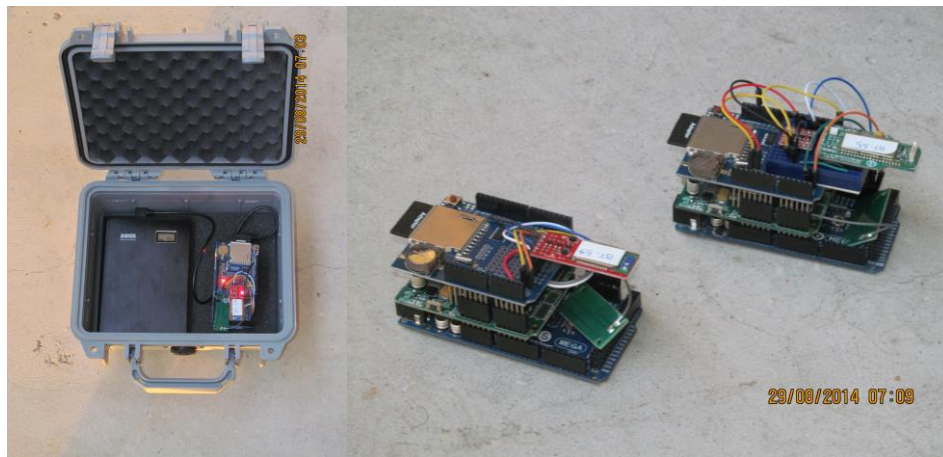
## 2.7 Verification of Simulation and Field Data Collection for Close Range

Two sets of field data were collected to verify simulation. The first set is collected when the master and slave are in close proximity (i.e.  $d \approx 0$ ) and is used to verify the simulation of the Bluetooth protocol without the influence of the location based detection probability model. The second data set was collected to verify the effect of distance and devices in a moving vehicle.

### 2.7.1 Hardware for Close Range Data Collection

The purpose of the first field data set was to validate the simulation of the Bluetooth inquiry protocol. This required detailed information about the timing of the inquiry process. However, most commercially available Bluetooth detectors do not provide this detailed information and therefore, we developed a custom Bluetooth detector that gathers detailed Bluetooth data and transmits these data over the internet to a server. A server side application was developed to receive, process and store the collected data in an SQL database. These data were then used for the verification process.

In order to observe the impact of different Bluetooth chipsets, two separate detectors (D1 and D2) were developed. The first (D1) utilizes RN41XV a class 1 Bluetooth module manufactured by Roving Network©. The second (D2) utilized WT41 a class 1 Bluetooth module manufactured by Bluegiga©. Both detectors utilize an ARDUINO® board as the main board which is based on an ATMEL ATmega® processor. Each detector is programmed to perform an inquiry scan and the start time of each inquiry window is recorded. Then we process the discovered MAC addresses which have responded to the inquiry packets. MAC address and details of the timing of discovery of each device is also recorded and stored in a SD memory card. The collected information is transferred to a communication module which uses cellular network (GSM/GPRS) or LAN to transfer the data in real-time to our server through the UDP protocol. It also sends a status report message to the server, every five minutes to report the status condition of the detector. Figure 2-6 shows the two developed detectors.



**Figure 2-6: Developed Bluetooth**

### 2.7.2 Close Range Data Collection Methodology

The purpose of the close range data set is to validate our simulation of the Bluetooth inquiry process. We conduct the validation by comparing (i) the time of detections within each master inquiry cycle and (ii) the time difference between two consecutive hits.

In order to carry out these comparisons we collected the Close Range field data as follows:

The two custom Bluetooth detectors were used separately. Eight Bluetooth equipped devices were used in the process (2 laptops, 3 tablets, and 3 smartphones). We tried to have a diversity of devices in terms of their characteristics such as hardware vendor, generation of Bluetooth technology, class of Bluetooth, and operating systems. All devices were placed a distance of less than 1 meter from the detectors.

$T_{w\_inquiry}$  was set to 5.12s. In order to minimize the effect of any random synchronization between the internal clock of devices and detector and make hardware test to match the simulation process, we configured the detectors to stop the inquiry process after a random number of  $T_{w\_inquiry}$  inquiry windows (1 to 6). Then after finishing each set of inquiries the detector sleeps for a random amount of time (uniformly distributed between 25 seconds to 30 seconds). This would remove any time synchronization between devices.

Furthermore, data were collected in different days and time of day. In this process 22,957 hits were collected.

### 2.7.3 Analysis of Close Range Data

Figure 2-7 shows relative frequency histograms for a sample of the Close Range data set. The X axis depicts the time of detection in the master's cycle. Data are grouped into 0.1 second bins. The Y axis depicts the relative frequency of each group.

Figure 2-7 a and b are the results from the two different detectors but the same Blackberry smartphone (utilizing a Texas Instruments© WL1273L wireless module). Comparing these two figures, it is evident that the two detectors exhibit different detection patterns even when detecting the same device. Detector D1 had a relatively high proportion of very short detection times ( $27\% \leq 0.5$  seconds) while Detector D2 provided only  $10\% \leq 0.5$  seconds. However, this behavior is not a consistent characteristic of the detector. For example, for some other devices,

such as a Dell tablet (Figure 2-7 c and d) the two detectors exhibit distributions of time to detection which are much more similar.

A comparison of Figure 2-7a and Figure 2-7c shows the distribution of detection time results for different slave devices (Blackberry Z10 versus Dell tablet) by the same detector (Detector D1). The pattern of detection is also different for these slave devices. Comparison of b and d confirm the same result.

It is evident that the Bluetooth devices might have differences in their implementation of the Bluetooth protocol which may cause some significant differences in the inquiry results. This variation might be a result of the manufacturer's implementation and choice of policies such as power management, random back off time, etc. that can influence the performance of detection. Issues such as power management are likely of more significant in devices such as mobile phones and therefore we anticipate larger variations in the inquiry process across various mobile devices. Moreover, some other factors such as the number of slaves around the master has an influence on the number of responses that the master receives in each inquiry window (Cabero et al. 2014).

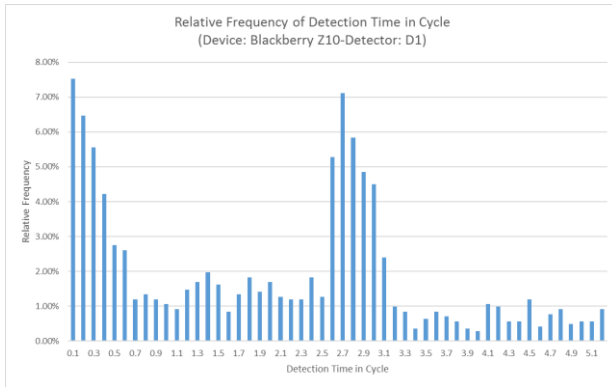
#### **2.7.4 Simulation of Close Range Data Collection**

The simulation model was developed as described in this chapter. We used the Vissim micro traffic simulation model to represent the movement of vehicles along a hypothetical roadway. The Close Range data set was collected with all devices in close proximity to the detectors. As such, the Close Range data set avoids the influence that distance from the detector has on reducing the probability of detection. In order to conduct a valid comparison between the simulation and the Close Range data set, we assumed that maximum range of Bluetooth devices is 100m and that the probability of detection at any location within this detection zone is 0.5 (i.e. there is no degradation in the probability of detection as a function of distance from the detector).

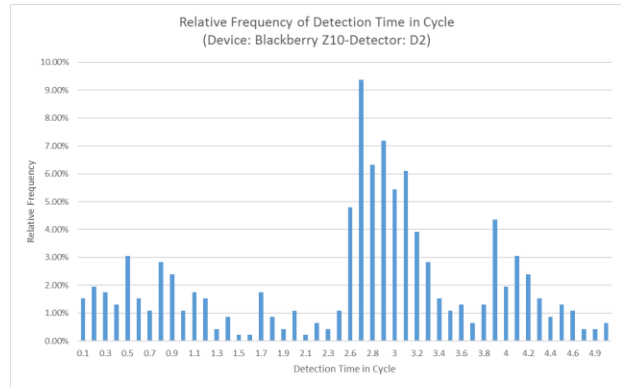
Figure 2-7 e shows the comparison of relative distribution of the time of detection in the master's inquiry cycle for the simulation and the Close Range field data for all devices. The simulation model results suggest that though there are small differences, particularly for very short times of detection, the simulation results show considerable similarities to the field data.

The minor differences arise because the simulation model assumes similar behavior among the devices and therefore suggests that the chance of detection is distributed uniformly in each 1.28 seconds.

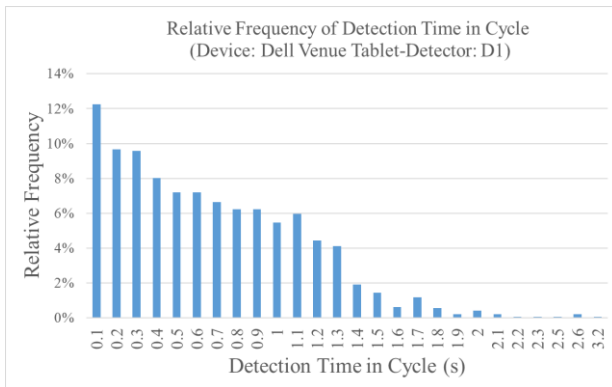
Figure 2-7 f shows that the distribution of the time between two consecutive hits for the simulation are very similar to the corresponding distribution from the Close Range data set.



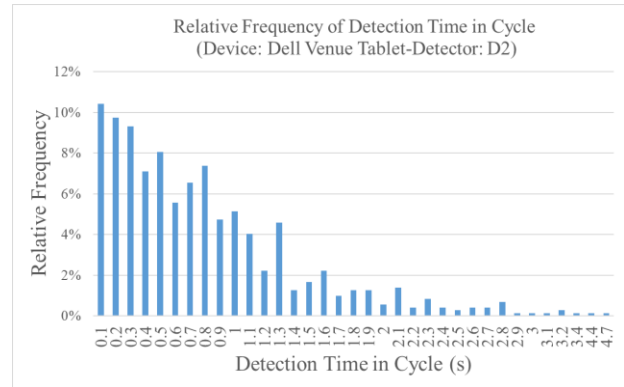
(a)



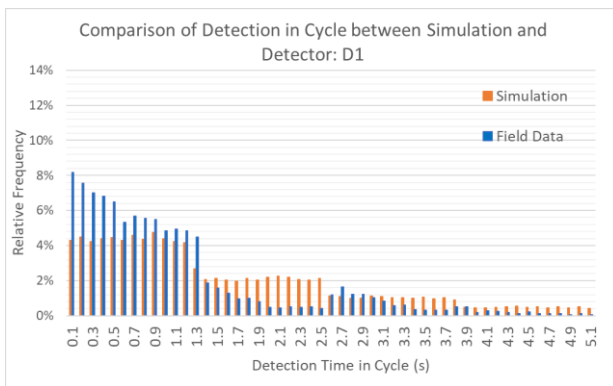
(b)



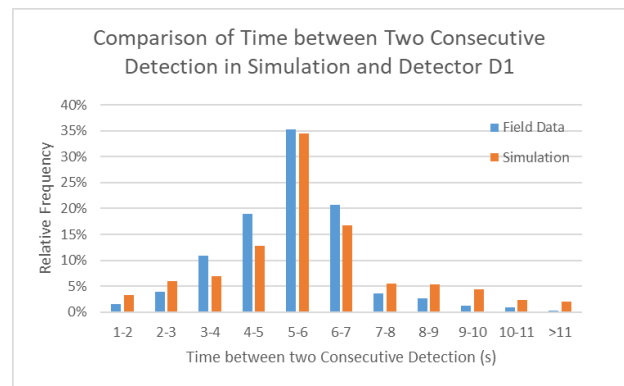
(c)



(d)



(e)



(f)

**Figure 2-7: Results of simulation model validation using close range data**



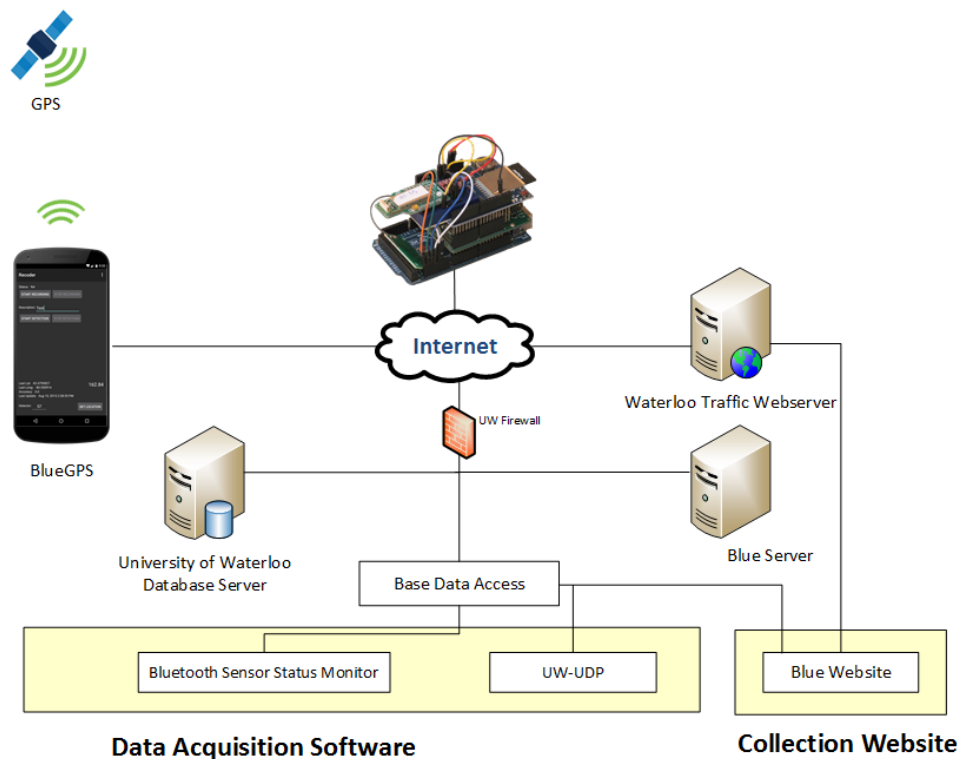
## 2.8 Verification of Simulation and Field Data Collection Considering Effect of Distance from Detector

In the previous section, we verified that the simulation framework can model the Bluetooth protocol when the device is in close proximity to the detector. In this section we want to verify if the proposed simulation framework is able to model the Bluetooth detection process when distance from the detector varies. Therefore, a second field data collection was performed.

In order to verify the proposed model, we need the location of each hit. Therefore, we require a platform to collect location information from Bluetooth devices along with the Bluetooth detections and match the location of each hit.

### 2.8.1 Developed Platform for Field Data Collection

Figure 2-8 shows the developed platform for the field data collection.



**Figure 2-8: Developed platform for filed data collection**

The Bluetooth detector D1 was equipped with an external 8 dBi antenna and was installed at a height of 1.8 meters. The same information as collected in the Close Range data collection

was collected and sent over the internet using a GSM/GPRS modem to the server. Figure 2-9 shows the setup of the developed hardware.



**Figure 2-9: Hardware deployment for Variable Range Field Data Collection**

The second part of this platform is recording the location of hits. We need a high resolution and accurate GPS tracker. Moreover, as the primary goal of this data collection was to match location of hits it was necessary to have the time synchronized between the server, the GPS tracker, and the Bluetooth detector.

Therefore, we developed a GPS tracking app, BlueGPS, for Android® to collect GPS coordinates. The app can record the location of the phone every 1 second and send the information to the server in real time. The app can calculate the distance to the detector in real time and shows the information to the driver.

The server application, UW-UDP was developed to receive this information in real time, store data in data base, and calculate the require parameters in real time.

### **2.8.2 Data Collection Procedure**

Two sites in the city of Waterloo, Ontario, Canada were selected for this data collection. Nine devices were used in this data collection (1 laptop, 1 GPS, 1 tablet, and 6 cellphones).

At the start of each data collection effort, the location of the detector was entered into the BlueGPS app which sent the location to the server. Then, the driver installed the tracking cell phone on the dash in the vehicle. The app shows the distance to the detector and records each trip. Then the driver drove the car from a point outside of the detector zone, through the detection zone, and then exited the detection zone.

In order to investigate the situation on arterials and stops at intersections, data were collected from two types of trips. The first was trips at a constant speed ranging from 10 to 60 km/h. The second was trips in which the vehicle stopped at one, two, or three locations (upstream of the detector) at different distances (90, 75, 50, 25 and 10 meters) from the detector and each stop varied from 1 to 120 seconds in duration.

The location information was recorded and sent to the BlueServer server by the BlueGPS app in real time and the clock of the cellphone was synchronized with the server. The Bluetooth hits were recorded by the detector and sent to the server in parallel in real time. The UW-UDP program matched them and recorded them to the SQL database.

Once the car entered the detection zone of the detector, the app starts a new detection for each device and once it exited the detection zone the detection is marked as completed. All the hits and the associated GPS points are recorded in trip detail table. Moreover, the time that each Bluetooth device entered and exited the detection zone, passed the detector, duration of trip, average speed of trip, time of first the hit, last hit, number of hits for each Bluetooth device is recorded in the detection table.

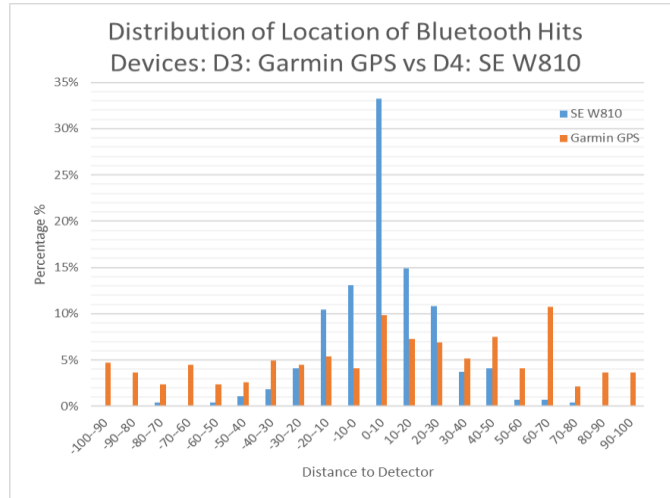
All data were recorded in real time and were available to the data collection team through the collection website and they could monitor the data collection in real time. A total 75 trips were made across the detection zone resulting in 433 detections and 3,123 hits.

The collected data provide the time and GPS location of each hit, detailed detection information, and the information of detector scan cycles. In the next section we use these detailed data to investigate and verify the proposed simulation methods and parameters.

### **2.8.3 Field Data Collection Result**

Investigation of collected data show that the class of device has a significant effect on the distribution of location of hits. Figure 2-10 compares the location of hits for two devices: a

class one Bluetooth device (D3: Garmin GPS Nuvi 2595) and a class two device (D4: SonyEricsson W810). These devices were carried together in the same vehicle at the same time through the detection zone of the detector for 75 times. As is evident from the results, these devices have different characteristics and the patterns of detection are different for these devices.



**Figure 2-10 Comparison of location of Bluetooth hits between class one and class two devices**

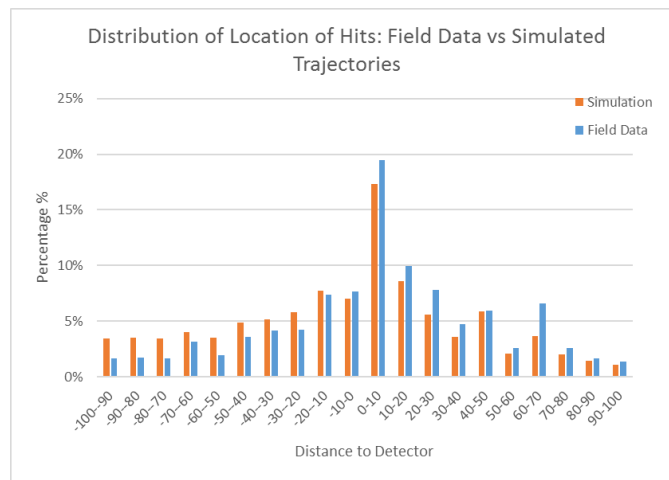
These differences are caused by variations in the implementation of the Bluetooth protocol parameters (which is discussed in the previous section) as well as the effect of distance.

In order to model the effect of distance on detection behavior, we propose two location based detection probability models representing class one and class two devices based on collected field data. In order to model the differences in Bluetooth protocol implementation, we used two Scan intervals (1.28s and 2.56s). As a result, we model four different types of devices as indicated in Table 2-2.

**Table 2-2 Location Based Detection PROBABILITY PARAMETERS**

Type	MR	R	Pr	ER	Per	Scan Interval	Portion
1	100	80	0.1	50	0.5	1.28	25%
2	100	80	0.1	50	0.5	2.56	25%
3	75	50	0.1	10	0.5	1.28	25%
4	75	50	0.1	10	0.5	2.56	25%

In order to verify the proposed simulation method with the devices and parameters in Table 2, trajectories obtained during the field data collection were fed to the developed simulation software and the Bluetooth hits were generated for the exact same trajectories. Figure 2-11 shows the comparison of generated Bluetooth hits from simulation and the collected data. The average absolute error is 2 percent indicating that the proposed simulation method provides a reasonably accurate model of the real world.



**Figure 2-11 Comparison of location of Bluetooth hits between simulated trajectories and field data**

## 2.9 Developed Software

As demonstrated in the previous section, the location of the first and last detection of a Bluetooth device is highly dependent on the pattern of the vehicle trajectory which is a function of the traffic characteristics. Therefore, a simulation software is developed to model the detection of Bluetooth detection. This software, Blue Synthesizer, utilizes the Vissim traffic micro-simulation model for simulating vehicles as they progress through a road network and interact with other vehicles and traffic control devices such as traffic signals. The Blue Synthesizer simulation software can interact with Vissim in either an *Offline* or an *Online* mode. In the offline mode, the Vissim model is run to generate a set of vehicle trajectories. These trajectories are stored in a data base and then used as input to BlueSynthesizer which generates simulated Bluetooth hits and detection records. In The online mode the Blue

Synthesizer software interacts with Vissim in real-time to generate the simulated Bluetooth detections while the Vissim simulation is executing. This online mode provides the ability to evaluate the performance of various advanced traffic management strategies (e.g. adaptive signal control), that rely on Bluetooth measurements, while controlling for various factors such as traffic conditions, Bluetooth detector locations, level of market penetration of Bluetooth enabled devices, etc.

## **2.10 Conclusions**

We have developed a simulation framework using the Vissim traffic simulation environment to simulate the Bluetooth detection process. This simulation framework can be used as a test bed for evaluating advanced traffic management strategies that rely on Bluetooth measurements.

The proposed Bluetooth simulation model was validated using field measurements collected using a custom built system of hardware and software. The field data showed that:

1. Different Bluetooth enabled devices exhibit different patterns with respect to the location of detection. As a result, we incorporated a distribution of devices (with different characteristics) to more accurately reflect variations in the Bluetooth detection patterns.
2. The proposed Bluetooth simulation model provides a high level of accuracy of the Bluetooth detection process, both in terms of the time between successive detections and the distribution of the location of the detection.

These results suggest that that the proposed simulation model is suitable for evaluating traffic management strategies that rely on Bluetooth detections.

# **Chapter 3**

## **Estimation of Control Delay at Signalized Intersections using Bluetooth Detectors**

### **3.1 Introduction**

As mention in Chapter 1, regardless of the form of signal control that is used (fixed time, actuated, responsive, adaptive) intersection performance is usually quantified in the terms of average vehicle delay. Ironically, most existing signal control systems are not able to measure delay directly, so they estimate delay on the basis of measured vehicle counts using various types of models. These models introduce error in the delay estimation process, leading to sub-optimal operation of the intersection.

In recent years, Bluetooth detectors have been widely considered as an efficient and straightforward tool for measuring travel time and average travel speed both on freeways and arterials. However, very little research has been conducted to investigate the opportunity to estimate intersection approach delay using Bluetooth collected data. In this chapter, we propose and evaluate two methods to estimate average vehicle delay at signalized intersections using data obtained from Bluetooth detectors.

In order to verify the proposed methods, one of the developed detectors along with a custom developed GPS tracking app were used to collect field Bluetooth data and the trajectories of vehicles. This combined data were used to verify the proposed delay estimation models.

Moreover, several traffic scenarios have been tested using the developed simulation framework described in Chapter 2 (BlueSynthesizer) and the performance of the proposed delay estimation methods have been evaluated.

### **3.2 Delay**

The travel times that vehicles experience as they traverse an arterial can be decomposed into two parts, namely (1) free flow travel times; and (2) delays. In general, delays may occur at

the intersection as a result of the intersection control, or mid-link as a result of interference from turning vehicles from cross streets, bus maneuvers at bus stops, vehicles engaged in parking maneuvers when on-street parking is permitted, crossing pedestrians and cyclists, commercial vehicles making deliveries, etc.

The impact of traffic signal operations on vehicle's delay is illustrated in Figure 1-1. Vehicle  $\nu$ -1 arrives at the intersection when the traffic signal is green and therefore is able to proceed through the intersection without any delay.

On the contrary, vehicle  $\nu$ , which is traveling at the same speed as vehicle  $\nu$ -1, arrives at the intersection just after the signal turns red. As a result, vehicle  $\nu$  decelerates, and stops at the intersection. After the signal turns green again, vehicle  $\nu$  starts to accelerate, and reaches the desired cruising speed. As illustrated in Figure 1-1, the control delay that a vehicle (e.g. vehicle  $\nu$ ) experiences at intersection  $i$  ( $d_{i,\nu}$ ) is expressed as:

$$d_{i,\nu} = d_{i,\nu}^d + d_{i,\nu}^s + d_{i,\nu}^a \quad (3-1)$$

$$d_{i,\nu}^d = t_{i,\nu}^2 - t_{i,\nu}^1 - \frac{l_{i,\nu}^2 - l_{i,\nu}^1}{S_{ffs,j}^k} \quad (3-2)$$

$$d_{i,\nu}^s = t_{i,\nu}^3 - t_{i,\nu}^2 \quad (3-3)$$

$$d_{i,\nu}^a = t_{i,\nu}^4 - t_{i,\nu}^3 - \frac{l_{i,\nu}^4 - l_{i,\nu}^2}{S_{ffs,j}^k} \quad (3-4)$$

Finally, substituting Equations 1-2, 1-3, and 1-4 into Equation 1-1, we compute the control delay as

$$\Rightarrow d_{i,\nu} = t_{i,\nu}^4 - t_{i,\nu}^1 - \frac{l_{i,\nu}^4 - l_{i,\nu}^1}{S_{ffs,j}^k} \quad (3-5)$$

Where,

$d_{i,\nu}$  : Control delay for vehicle  $\nu$  at intersection  $i$  (second)

$d_{i,\nu}^d$  : Deceleration delay for vehicle  $\nu$  at intersection  $i$  (second)

$d_{i,\nu}^s$  : Stopped delay for vehicle  $\nu$  at intersection  $i$  (second)



$d_{i,v}^a$  : Acceleration delay for vehicle  $v$  at intersection  $i$  (second)

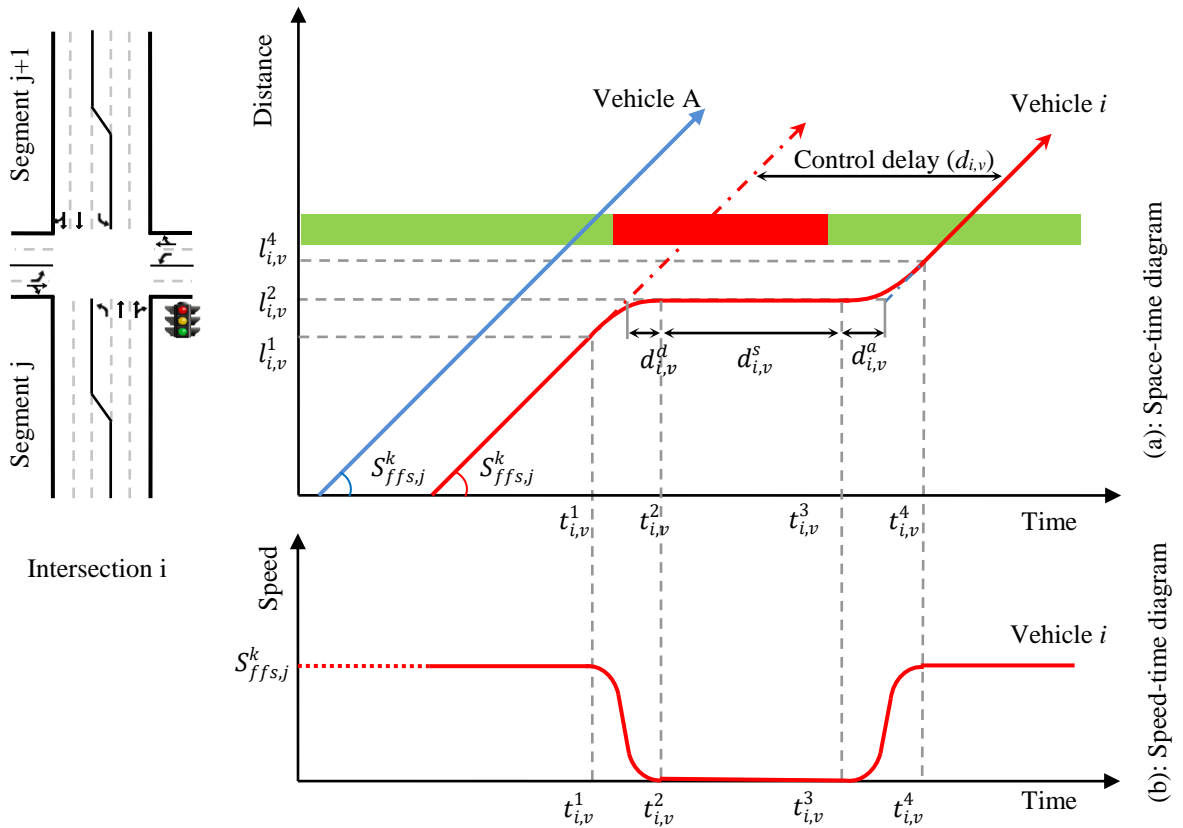
$t_{i,v}^1$  : Time that the  $v^{th}$  vehicle started to decelerate at intersection  $i$

$t_{i,v}^4$  : Time that the  $v^{th}$  vehicle reached its cruise speed at intersection  $i$

$l_{i,v}^1$  : Location that the  $v^{th}$  vehicle started to decelerate at intersection  $i$

$l_{i,v}^4$  : Location that the  $v^{th}$  vehicle attained the cruise speed at intersection  $i$

$S_{ffs,j}^k$  : Free-flow speed of segment  $j$  at time interval  $k$



**Figure 3-1: The effect of signal control and arrival time on intersection delay**

When demand is less than capacity, then all vehicles arriving during a single cycle are able to clear the intersection during the green interval. In this situation the approach is considered

to be under-saturated. When demand exceeds capacity, the approach is considered to be over-saturated.

The Highway Capacity Manual (2010) defines the average vehicle delay for each lane group as Equation (3-6) which is based on the original work by Webster (Webster 1958).

$$d = PF * d_1 + d_2 + d_3 \quad (3-6)$$

$$d_1 = \frac{0.5C(1 - g / C)^2}{1 - [\min(1, X)g / C]} \quad (3-7)$$

$$d_2 = 900T \left[ (X_A - 1) + \sqrt{(X_A - 1)^2 + \frac{8kIX_A}{c_A T}} \right] \quad (3-8)$$

Where,  $d_1$  is average overall uniform delay,  $d_2$  is average incremental delay<sup>1</sup> which accounts for the extra delay caused by the randomness of vehicle arrivals,  $d_3$  is initial queue delay,  $X$  is volume-to-capacity ratio,  $g$  is green time and  $C$  is cycle length,  $X_A$  is average volume-to-capacity ratio,  $c_A$  is Average lane group capacity,  $k$  incremental delay factor,  $PF$  is the progression factor, and  $T$  is analysis period duration.

The relationship between the average delay and the degree of saturation is illustrated in Figure 3-2 (assuming no initial queue i.e.  $d_3 = 0$ ). As demonstrated in Figure 3-2 when a lane group is operating at  $v/c$  of less than approximately 0.7, the control delay is dominated by the uniform delay component ( $d_1$ ). For values of  $v/c$  greater than approximately 0.9, the overflow delay ( $d_2$ ) is the dominant component.

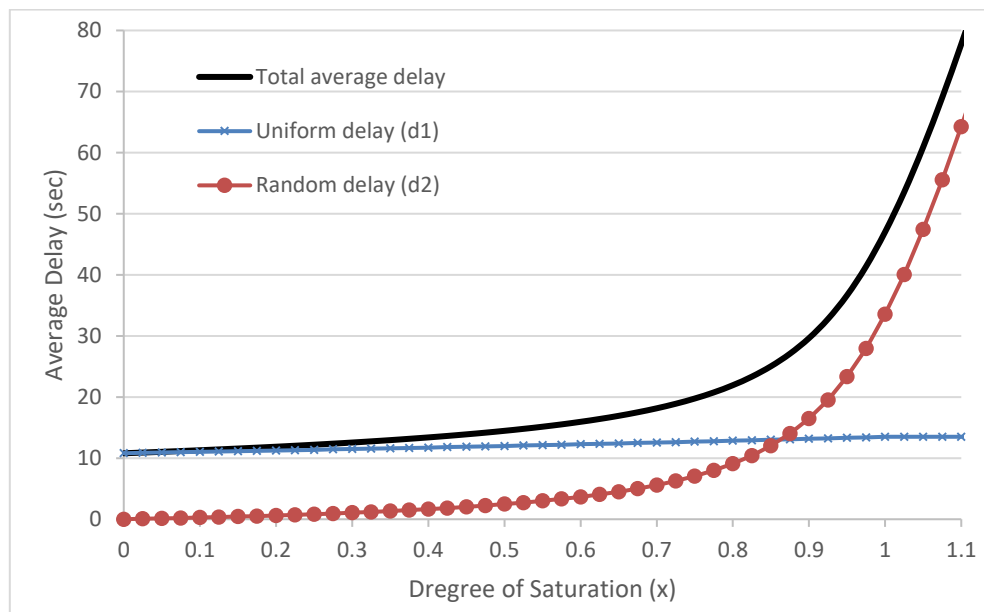
Delay is the most important measure of performance widely used in many existing Advanced Traffic Management Systems (ATMS) such as real time traffic signal optimization. The level of service (LOS) is a qualitative measure of traffic flow expressed based on the average vehicle delay of an intersection. The objective of traffic signal timing design process in Highway Capacity Manual (2010) and Canadian Capacity Guide (2008) is to minimize the delay and achieve better LOS. As a result, intersection delay is the most significant input parameter for

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<sup>1</sup> Also called random delay

design and optimization of traffic signal timing and evaluation of traffic operations at signalized intersections.

Most existing adaptive signal control systems are not able to measure delay directly, so they estimate delay on the basis of measured vehicle counts using models such as Equation (3-6) . These models were originally proposed as a means of developing fixed time signal timing plans and are generally considered to be adequate for describing average conditions; but they are not very accurate when attempting to estimate delays in real-time or for degree of saturation approaching or exceeding 1.



**Figure 3-2: Relative contribution of uniform and random delay to total delay (using HCM expressions)**

### 3.3 Bluetooth Detectors and Their Application in Transportation

In recent years, Bluetooth detectors have gained increasing attention as an efficient technology for measuring travel time and average travel speed on freeways and arterials. Travel time is calculated by the time difference of the matched MAC at successive detectors and average speed is computed on the basis of the travel time and the distance between the successive detector stations

In general, in recent years, most Bluetooth detectors have been used for acquiring travel time data for Advanced Traveler Information Systems (ATIS) and evaluation of traffic management projects, strategies and decisions (Haghani et al. 2010, Barceló et al. 2010, Bachmann et al. 2013).

A number of studies have been conducted to examine the accuracy of estimated travel time, quantifying measurement errors and detection of outliers (Haghani et al. 2010, Malinovskiy et al. 2011, Moghaddam, Hellinga 2013, Araghi et al. 2015).

More recently, more studies have been conducted to use Bluetooth technologies in short-term real-time prediction of travel times. Hu and Hellinga (2013) developed a prediction model for freeways. Moghaddam and Hellinga (2014) developed a robust method for prediction of travel time on arterials.

Day and Haseman (2010) developed a visual method for off-line assessment of progression on arterials on the basis of Bluetooth measurements. Essentially, they collected before data using Bluetooth detectors, examine the patterns to suggest changes to the offset and then collect data after the new offsets have been implemented in order to evaluate changes in quality of progression. Park and Haghani (2014) also proposed a method for offline optimization of signal offset using travel time and applied the optimized offset in a corridor.

However, it is possible to extract additional information from Bluetooth detections. The time stamp of the hits for each Bluetooth device provide additional information regarding the dwell time (e.g. the difference between the time stamps of the first and last hits for a Bluetooth device that traversed the detection zone). This dwell time can be used to evaluate the experienced delay for different movements in intersections.

### **3.3.1 Applying Bluetooth Technology for Delay Estimation**

To date, there are few studies that have used Bluetooth data for estimating delay. Abbas et al. proposed two models to estimate control delay on the basis of Bluetooth data (Abbas et al. 2013). They equipped probe vehicles with GPS trackers and collected GPS and Bluetooth data together. Using these data, they proposed two models to estimate control delay; one as a function of the number of hits and the second as a function of dwell time. However, their models suffer from the following limitations. First, they assume that all control delay occurs

within the Bluetooth detection zone. When queues extend beyond the effective range of the Bluetooth detector this assumption is violated and their models will under-estimate the control delay. We note that in their work, they had an effective detection range of approximately 500m or more. However, a more typical range with class 1 devices is approximately 100m. Second, it appears that their calibration data were collected from a single or just a few different Bluetooth devices. Previous work (Chapter 2) has shown that different Bluetooth enabled devices exhibit substantial variation in the Bluetooth detection process, which also impacts the relationships between number of hits and dwell time. Third, their model is based on a relatively small set of data (22 probe vehicle runs across a corridor with three Bluetooth detectors) consisting of only 66 observations.

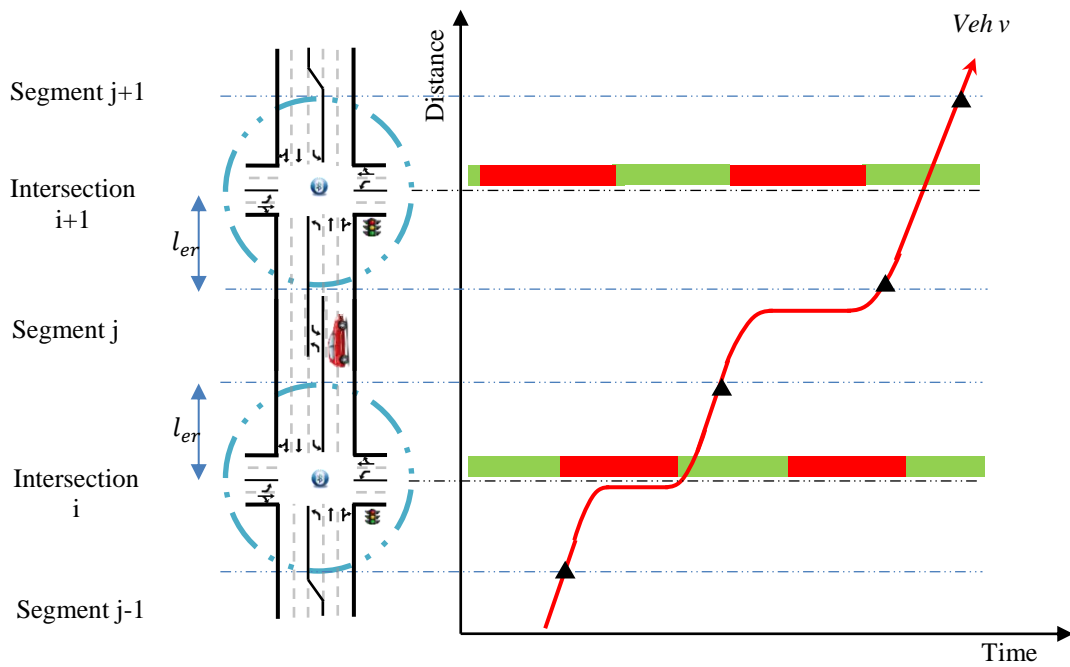
In this chapter, we present two models for estimating vehicle control delay from Bluetooth detector data that extends the work Abbas et al, and addresses the three limitations identified above.

### **3.4 Proposed methods for estimating delay using Bluetooth detector data**

Figure 3-3 shows a time-space diagram of a hypothetical vehicle ( $v$ ) traversing two signalized intersections ( $i-1$  and  $i$ ). The vehicle experiences delay due to the signal operations at each of the intersections. A Bluetooth detector is located at each intersection and the effective detection range is  $l_{er}$ . Assuming an idealized case, the first and last hit obtained for vehicle  $v$  at each intersection is shown as a solid black triangle.

At intersection  $i-1$ , the vehicle joins the stopped queue close to the intersection stop line and well within the effective range of the Bluetooth detector. At intersection  $i$ , the vehicle again experiences delay due to the traffic signal, however in this case, the queue is much longer and the vehicle joins the tail of the stopped queue upstream of the Bluetooth detection zone. In this case, the vehicle experiences control delay before it enters the Bluetooth detection zone and this delay cannot be captured by simply examining the dwell time or the number of hits obtained from the Bluetooth detector.

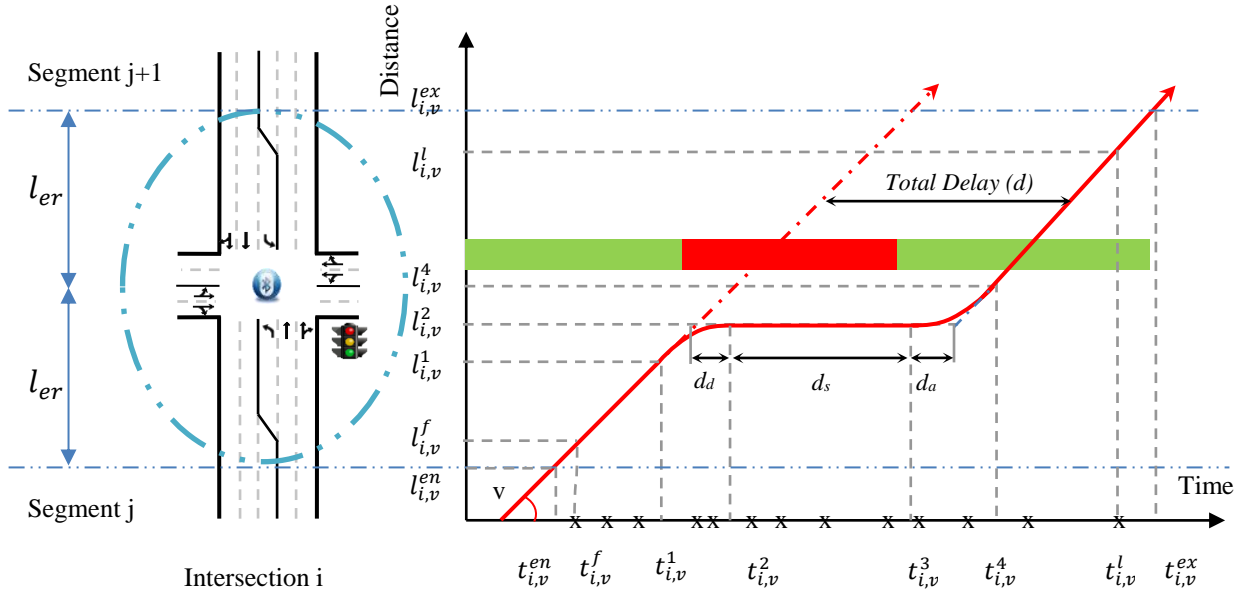
In the following sections, we propose two methods for these cases to estimate the delay for individual vehicles and average delay of movement groups for each approach at signalized intersections using Bluetooth technology.



**Figure 3-3: Sample trajectory of Bluetooth enabled vehicles**

### 3.4.1 Method 1: Queue length is less than range of Bluetooth detector

Figure 3-4 shows a time-space diagram of a hypothetical vehicle traversing road segment  $j$  and performing a through movement at intersection  $i$  and then traversing segment  $j+1$ . Now assume that this vehicle contains a detectable Bluetooth device and a Bluetooth detector is located at the intersection. The Bluetooth device in the vehicle is identified a number of times while the vehicle is within the detection zone. Each identification event is called a hit and provides the time of the identification, but does not provide any information regarding the location of the vehicle when it is identified. Therefore, Bluetooth hits are shown as crosses (x) on the Time axis.



**Figure 3-4: Bluetooth detection and sample trajectory of a vehicle**

We wish to estimate the delay experienced by the vehicle but we do not know  $t_{i,v}^4, t_{i,v}^1, l_{i,v}^1, l_{i,v}^l$  and therefore  $d_{i,v}$  cannot be directly calculated using Equation (3-5). Instead, we can redefine  $d_{i,v}$  as the delay vehicles experience within the detection zone of the Bluetooth detector and computed it as:

$$d_{i,v} = t_{i,v}^{ex} - t_{i,v}^{en} - \frac{l_{i,v}^{ex} - l_{i,v}^{en}}{(S_{ffs,j}^k)} = \Delta t_{i,v} - \frac{2l_{er}}{S_{ffs,j}^k} \quad (3-9)$$

Where:

$\Delta t_{i,v}$ : Time taken by vehicle  $v$  to traverse the detection zone of intersection  $i$  (True dwell time)

$t_{i,v}^{en}$ : The time when vehicle  $v$  entered the detection zone of intersection  $i$

$t_{i,v}^{ex}$ : The time when vehicle  $v$  departs the detection zone of intersection  $i$

$l_{er}$ : Length of effective range of Bluetooth detector

$l_{i,v}^{en}$ : The location of vehicle  $v$  (measured as the distance from the Bluetooth detector) when it entered the detection zone of intersection  $i$  ( $l_{i,v}^{en} = -l_{er}$ )

$l_{i,v}^{ex}$ : The location of vehicle  $v$  (measured as the distance from the Bluetooth detector) when it departed the detection zone of intersection  $i$  ( $l_{i,v}^{en} = l_{er}$ )

Bluetooth detections do not contain any information regarding the location of the vehicles. Therefore in these equations  $t_{i,v}^{ex}$  and  $t_{i,v}^{en}$  are not known. However, according to Chapter 2 and Moghaddam and Hellinga (Moghaddam, Hellinga 2013) we expect that these values are close to the time of first detection ( $t_{i,v}^f$ ) and last detection ( $t_{i,v}^l$ ) and the true dwell time ( $\Delta t_{i,v}$ ) can be estimated from the known Bluetooth dwell time ( $\Delta t_{i,v}^b$ ) as follows:

$$\Delta t_{i,v}^b = t_{i,v}^l - t_{i,v}^f \quad (3-10)$$

$$d_{i,v} = E(\Delta t_{i,v}^b) - 2 \frac{l_{er}}{S_{ffs,j}^k} \quad (3-11)$$

Where:

$t_{i,v}^f$ : Time of first detection of the  $v^{th}$  vehicle that passed intersection  $i$

$t_{i,v}^l$ : Time of last detection of the  $v^{th}$  vehicle that passed intersection  $i$

$\Delta t_{i,v}^b$ : Time difference of first and last detection of  $v^{th}$  Bluetooth enabled vehicle at intersection  $i$  (Bluetooth dwell time)

$E(\Delta t_{i,v}^b)$ : Relationship that estimates true dwell time from Bluetooth dwell time

In traffic management systems, we are usually interested in average delay of each movement group<sup>1</sup> during specific time intervals (typically 5 or 15 minute intervals). If there are Bluetooth detectors installed at upstream/downstream of each approach, then we would be able to determine the turning movement that each detected vehicle made and therefore we can allocated the estimated delay to a specific movement group. Under these conditions at the end of each polling interval the average delay of each movement group in each approach can be estimated using Bluetooth detector data as follows:

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<sup>1</sup> We call movements from each approach that discharge at the same time at each phase a movement group.



$$\bar{d}_{i,j,mg}^k = \frac{1}{n_{i,j,mg}^k} \sum_{v=1}^{n_{i,j,mg}^k} [d_{i,v}] = \frac{1}{n_{i,j,mg}^k} \sum_{v=1}^{n_{i,j,mg}^k} \left[ \Delta t_{i,v}^b - 2\alpha_m \frac{l_{er}}{S_{ffS,j}^k} \right]$$

$$\Rightarrow \bar{d}_{i,j,mg}^k = \frac{1}{n_{i,j,mg}^k} \sum_{v=1}^{n_{i,j,mg}^k} [E(\Delta t_{i,v}^b)] - 2 \frac{l_{er}}{S_{ffS,j}^k} \quad (3-12)$$

Where:

$\bar{d}_{i,j,mg}^k$ : Average delay of movement group  $mg$  in segment  $j$  at intersection  $i$  during time interval  $k$

$n_{i,j,mg}^k$ : Number of Bluetooth enabled vehicles from segment  $j$  which were in movement group  $mg$  at intersection  $i$  during time interval  $k$

### 3.4.2 Method 2: Queue length may be greater than range of Bluetooth detector

The method proposed in the previous section for estimating delay is valid only if the queue length is less than the effective range of Bluetooth detector (which is usually assumed to be 100 meters). In this section, we propose a method for estimating delay when we expect the queue length may be greater than the effective range of the Bluetooth detector.

Figure 3-5 shows a time-space diagram of a hypothetical vehicle ( $v$ ) traversing segment  $j$  and performing a through movement at intersection  $i$  and then traversing segment  $j+1$ . Vehicle  $v$  encounters a queue more than length effective range ( $l_{er}$ ). In this case, we redefine the delay as the difference between the travel time that this vehicle experiences over the segment  $j$  ( $tt_{ll,v}^j$ ) and its desired travel time over segment  $j$  ( $tt_{FFS}^j$ ) as follows:

$$tt_{ll,v}^j = t_{i,v}^l - t_{i+1,v}^l \quad (3-13)$$

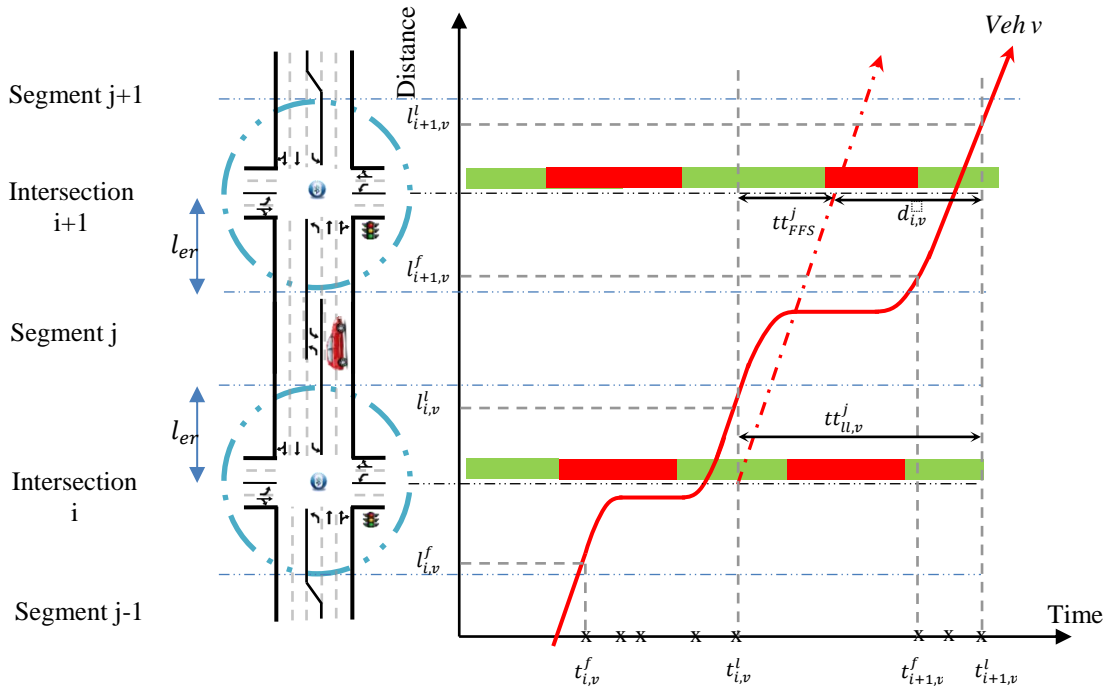
$$d_{i,v} = \max(tt_{ll,v}^j - tt_{FFS}^j, 0) \quad (3-14)$$

Where:

$t_{i,v}^l$ : Time of last detection of the  $v^{th}$  vehicle that passed intersection  $i$

$tt_{ll,v}^j$ : Travel time of the  $v^{th}$  vehicle in segment  $j$

$tt_{FFS}^j$ : Free flow travel time of vehicles over segment  $j$



**Figure 3-5: Bluetooth detection and sample trajectory of a vehicle when queue is greater than effective range**

If the free flow speed of the segment is unknown, a typical substitute would be to use the posted speed limit. Another method that we used in this chapter is to estimate the free flow travel time as the 15<sup>th</sup> percentile of the Bluetooth travel time for all vehicles that passed during the past set time period (e.g. hour). This method permits the free flow travel to be dynamically estimated in real time. This may be particularly valuable when free flow travel times are expected to change such as when adverse weather conditions exist.

Therefore, the average control delay of each movement group can be calculated as:

$$\bar{d}_{i,j,mg}^k = \frac{1}{n_{i,j,mg}^k} \sum_{v=1}^{n_{i,j,mg}^k} d_{i,v} \quad (3-15)$$

In order to estimate a vehicle delay using this method, we need to have an upstream Bluetooth detector at each approach. Figure 3-5 shows a sample configuration for this method. The upstream detector could be installed at intersection or can be installed in a mid-block

location. However, there should not be any signalized intersection between the upstream detector (intersection  $i$ ) and the downstream detector (intersection  $i+1$ ). Moreover, there should not be any spillback from the downstream intersection into the upstream intersection. If such spillback occurs, the control delay estimated for the upstream intersection will be over-estimated (as it will include the delay experienced downstream of the upstream intersection) and this will adversely impact the green split optimization process.

Equation (3-12) and (3-15) provide the opportunity to make a direct estimate of average vehicle delay for each movement group, rather than having to estimate delay on the basis of estimated traffic volumes. These estimates of delay are an essential input for offline or real-time traffic signal control optimization.

In the following sections we investigate the validity of this method using a field test and simulation data and validate the relationship between true dwell time and Bluetooth dwell time. We also compare the accuracy of the proposed methods.

### **3.5 Field Data Collection**

The collected field data described in the previous chapter were used to satisfy the following two requirements:

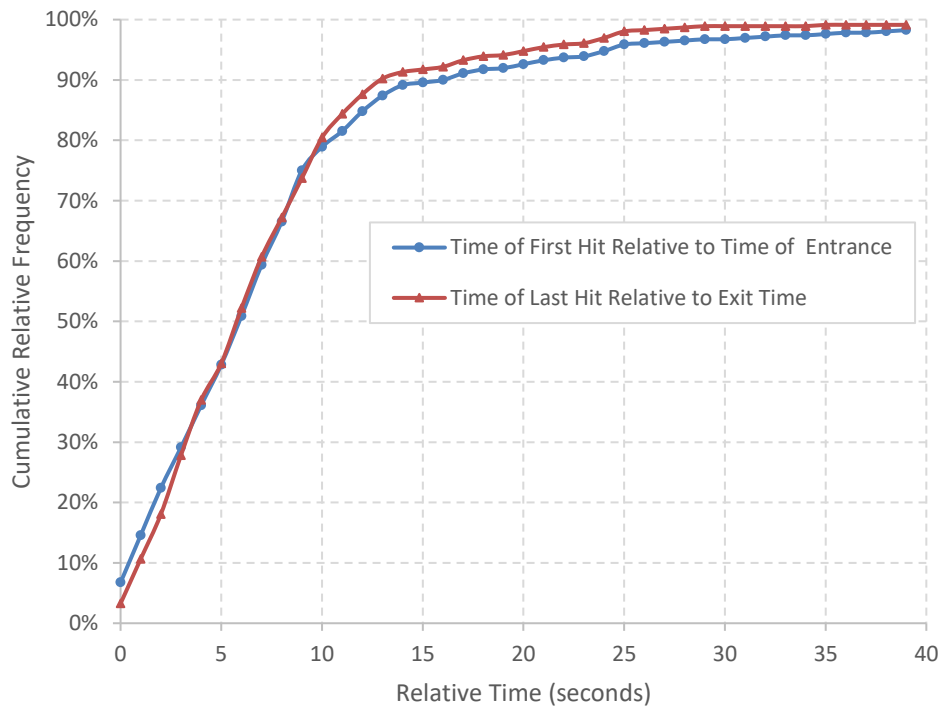
1. Calibrate and validate Method 1 and establish  $E(\Delta t_{i,v}^b)$ , the relationship between Bluetooth dwell time and the true dwell time;
2. Validate the Bluetooth simulation model which is subsequently used to evaluate the accuracy of both Method 1 and Method 2 for a range of conditions.

The collected data provide the time and GPS location of each hit, detailed detection information, and the information of detector scan cycles. In the next sections, we use these detailed data to investigate and verify the proposed delay estimation methods and simulation parameters.

### 3.5.1 Field Data Analysis and Results

Figure 3-6 shows the cumulative relative frequency distributions of the time of the first/last hit relative to the time that the vehicle entered/exited the detection zone. We make the following two observations:

1. The two distributions (i.e. for first hit/entry time and for last hit/exit time) are very similar. This result is expected.
2. The times between entry and the first hit or between the last hit and exit exhibit substantial variation. We observe that for 20% of the observations, the difference is greater than 10 seconds and for 10% the difference is greater than 15 seconds. We will see that these differences essentially amount to measurement errors.

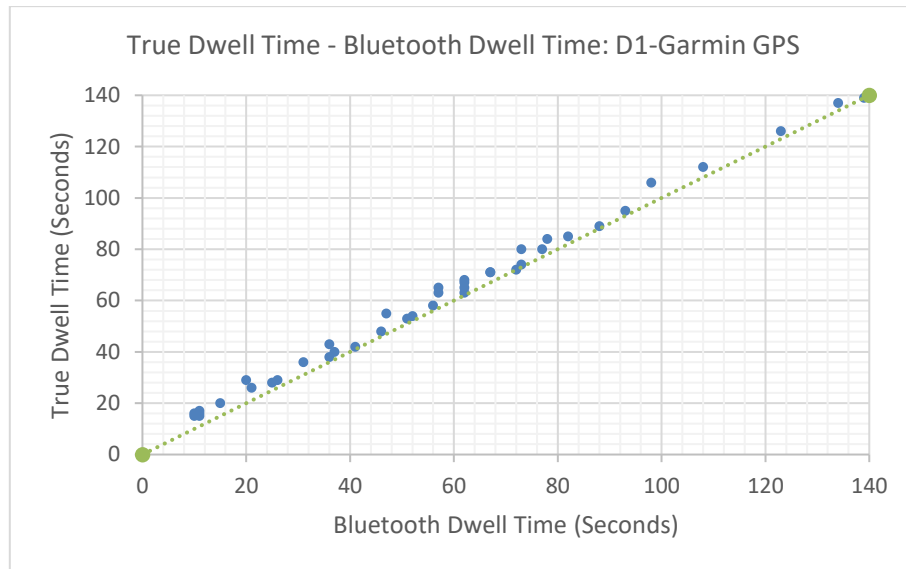


**Figure 3-6: Distribution of Time of First/ Last Hit Relative to Time Vehicle Entered/Exited Detection Zone**

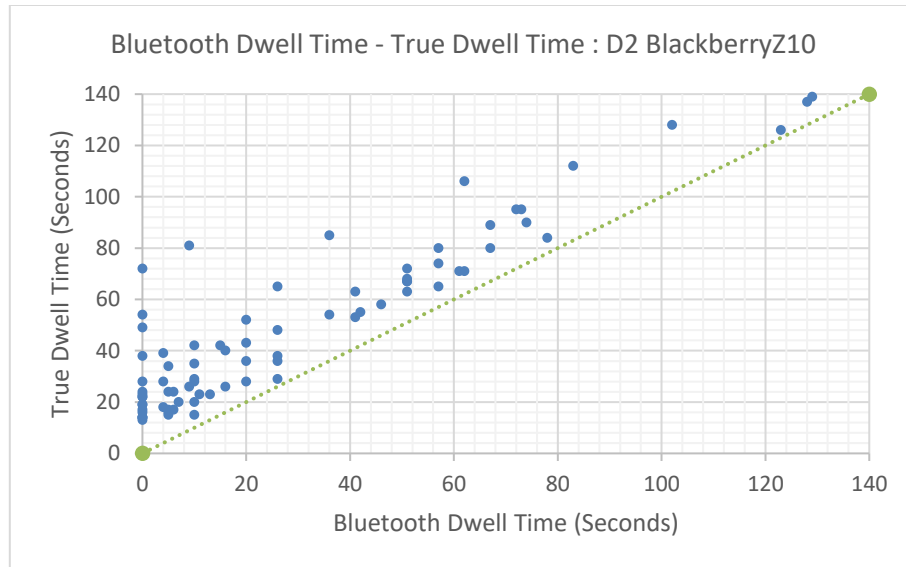
Figure 3-7 shows the measured Bluetooth dwell time and the true dwell time (as obtained from the GPS data) for two different Bluetooth enabled devices. The dotted gray line represents a line of perfect correlation. The data were collected for both devices under the same set of

conditions; however, the results show that the level of correlation between the measured Bluetooth dwell times and the true dwell times are substantially different between the two devices.

Note that because the two devices experienced the same conditions, it might be expected that both graphs should depict the same series of true dwell times; however, a careful examination shows that they do not. For some runs, both devices were detected while for others, only one device was detected. Consequently, when both devices were detected, the true dwell times appear in both graphs and are equal. However, when only one device is detected, this true dwell time does not appear in the graph for the non-detected device. Additionally, a Bluetooth dwell time equal to zero indicates that only a single hit was obtained for that device during that run.



(a) Device = Garmin GPS Nuvi 2595



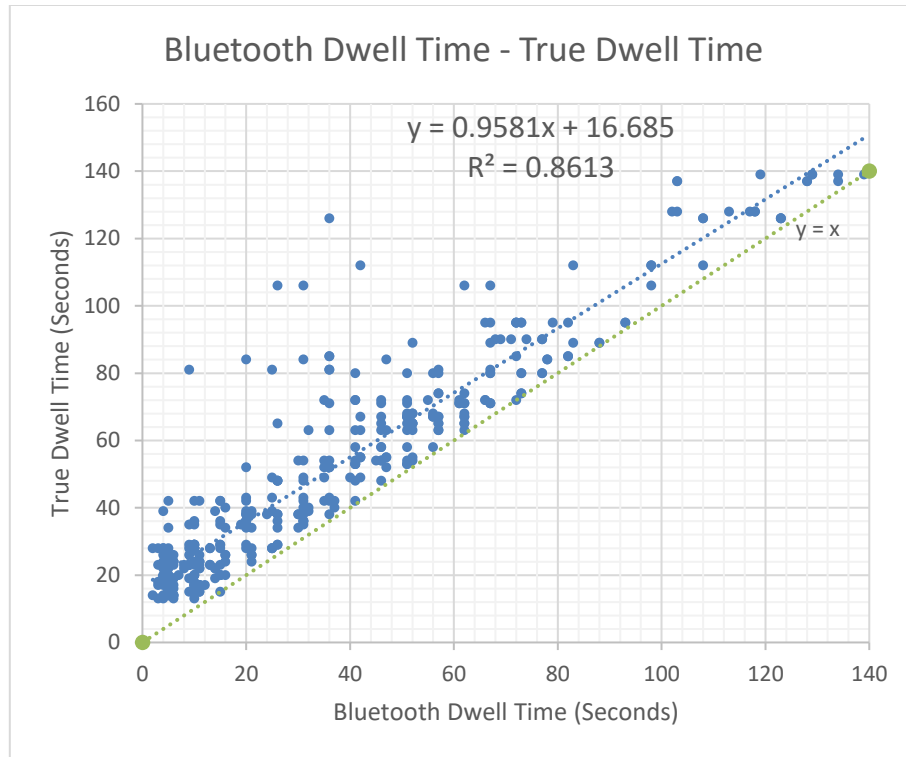
(b) Device = Blackberry Z10

**Figure 3-7: Bluetooth dwell time versus true dwell time for two different devices**

Figure 3-8 shows the collected data from all of the eight devices<sup>1</sup> and the relationship between the true dwell time ( $\Delta t_{i,v}$ ) and the Bluetooth measured dwell time ( $\Delta t_{i,v}^b$ ). As expected, there is a strong linear relationship between the true dwell time and Bluetooth measured dwell time and that the Bluetooth measured dwell times consistently underestimate the true dwell time.

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<sup>1</sup> Observations for which the Bluetooth dwell time was zero have not been used when developing the regression model.



**Figure 3-8: Collected Field Data showing the Relationship between Bluetooth Dwell Time and True Dwell Time**

A linear regression model was calibrated to the data as a means of estimating the true dwell time on the basis of the measured Bluetooth dwell time. This model (provided in Equation (3-16)) explains a large proportion of the variance exhibited in the data ( $R^2 = 0.86$ ) and both the slope and intercept are statistically significant (Table 3-1).

$$\Delta t_{i,v} = E(\Delta t_{i,v}^b) = 0.96\Delta t_{i,v}^b + 16.69 \quad (3-16)$$

**Table 3-1: Analysis of Regression  $\Delta t_{i,v}$  and  $\Delta t_{i,v}^b$**

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	18.46	0.849	21.72	3.49E-71
Coefficient for $\Delta t_{i,v}^b$	0.93	0.018	49.61	4.80E-180

The analysis of the field data has shown that as proposed by Abbas et al (Abbas et al. 2013) there is a linear relationship between the true dwell time and the measured Bluetooth dwell time. However, we have also shown that the nature of this relationship and the degree of correlation is dependent on the type of device. Furthermore, in practice, we are interested in estimating control delay rather than the true dwell time.

Measuring the true control delay in the field is difficult, as it requires detailed trajectory data for all vehicles that traverse the approach. Furthermore, we want to be able to conduct the evaluation over a wide range of traffic conditions including those for which queues extend beyond the effective range of the Bluetooth detectors. As a result, we carry out the validation of the proposed control delay estimation methods using a custom build simulation platform. This is described in the next section.

## **3.6 Validation Using Simulation**

### **3.6.1 Simulation Framework**

*BlueSynthesizer* is able to model the Bluetooth detector inquiry scan process and the effect of distance from the detector on the inquiry process. *BlueSynthesizer* simulates both the Bluetooth detector and the Bluetooth enabled vehicles (devices). It simulates the internal clock of both the detectors and the devices and the scan intervals of the devices. At each scan interval of each device, the simulation calculates the distance of device to the detector and determines the likelihood of detection based on a location based detection probability function.

### **3.6.2 Validation of the *BlueSynthesizer* Model Using Field Data**

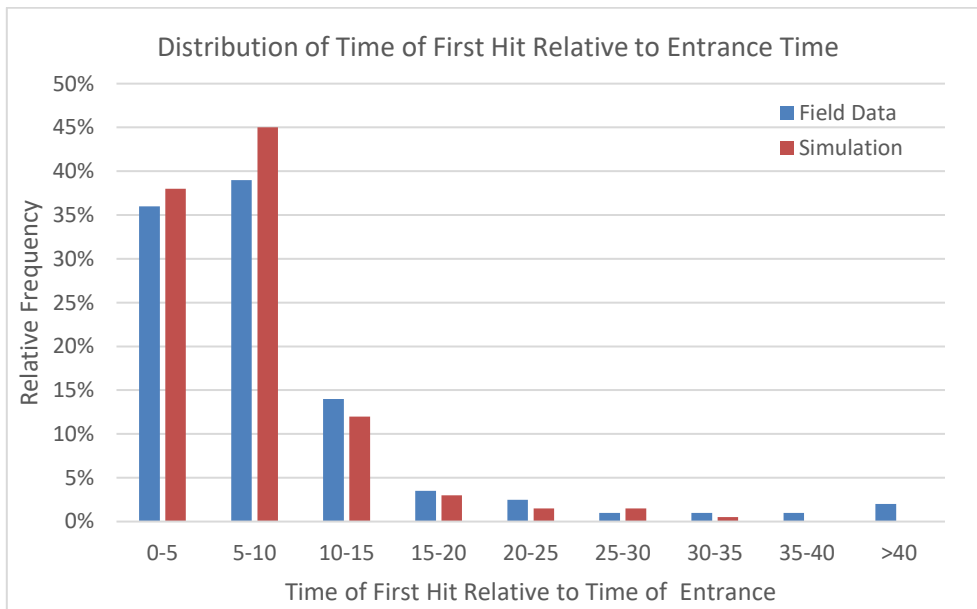
In Chapter 2, we showed that the proposed Bluetooth simulation model provides a high level of accuracy of the Bluetooth detection process, both in terms of the time between successive detections and the distribution of the location of the detection.

The accuracy of the measured Bluetooth dwell time as an estimate of the true dwell time is primarily a function of the error between the time of the first hit and the time when the vehicle enters the detection zone and the time of the last hit and the time the vehicle leaves the detection zone. In section 3.5.1 we showed the distribution of these measurement errors from the field data. We provided *BlueSynthesizer* with the GPS trajectories recorded from the field data

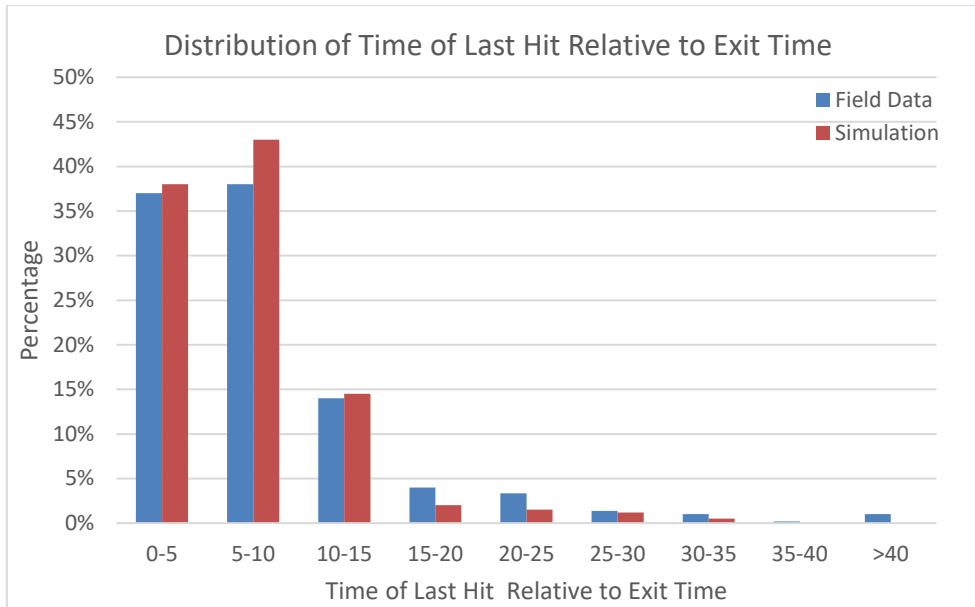


collection and then generated simulated Bluetooth detection data. From these simulated data, we computed the same measurement errors.

Figure 3-9 compares the distribution of the time of the first hit relative to the time of entrance between field data and simulated trajectories and Figure 3-10 compares the distribution of the time of the last hit relative to exit time between field data and simulated trajectories. The X axis depicts the relative time of first/last hit relative to time the vehicle entered/exited the detection zone. Data are grouped into 5 second bins. The Y axis depicts the relative frequency of each group. The average absolute error in both is less than 4%. This shows the simulation framework can simulate the Bluetooth detection process.



**Figure 3-9: Comparison of Distribution of Time of First Hit Relative to Time of Entrance**



**Figure 3-10: Comparison of Distribution of Time of Last Hit Relative to Exit Time**

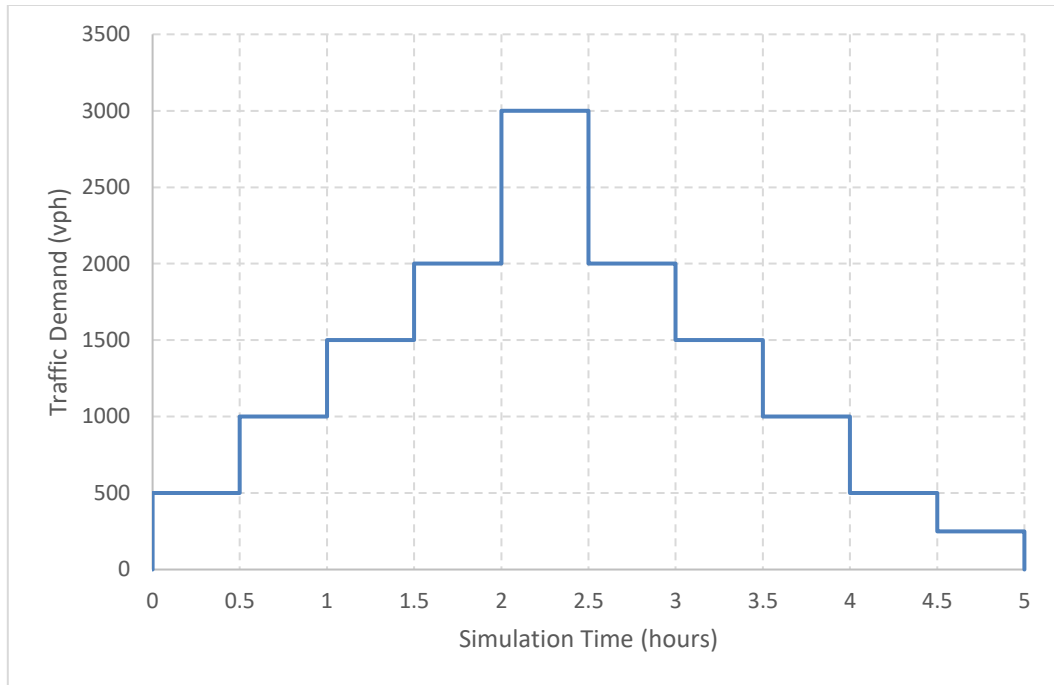
### 3.7 Validation of Proposed Control Delay Estimation Methods

In this section, we describe the use of the simulation framework described in the previous section to evaluate the performance of the proposed methods for estimating control delay.

We first describe the hypothetical network and traffic conditions that were simulated. Then we examine the accuracy of the proposed methods for estimating control delay by comparing the estimates to the actual delays as extracted from the simulation model.

#### 3.7.1 Simulation Network

A one way two-lane arterial roadway containing two signalized intersections 500 meters apart was modelled. Each traffic signal operated under two-phase fixed time control. A total of 18 simulation scenarios were defined. Each scenario was replicated 5 times using different random seed numbers. We controlled four traffic factors at each intersection, namely: (1) degree of saturation; (2) cycle length; (3) green interval duration of main corridor; and (4) quality of progression. The duration of each simulation was 5 hours. The traffic demands varied over time as shown in Figure 3-11.



**Figure 3-11: Temporal variation in traffic demand**

The cycle length of the upstream intersection ( $i$ ) was set to  $\{90, 120, 180\}$  seconds and the  $g/C$  was selected from  $\{0.45, 0.5, 0.65\}$ . The downstream intersection ( $i+1$ ) cycle length was accordingly set to values  $\{60, 90, 120\}$  seconds and the  $g/C$  was selected from  $\{0.5, 0.65, 0.8\}$ . Three levels of progression were modelled, namely: well-coordinated, moderate coordinated, and poorly coordinated. Coordination was controlled by varying the offset of the downstream signal relative to the upstream signal.

The network was simulated using the abovementioned scenarios and trajectories of vehicles were extracted. *BlueSynthesizer* generated the Bluetooth hits, detections and calculated the travel times using the trajectories. The maximum queue length information was recorded for each 5-minute interval and estimated delay was calculated using the two proposed methods. For Method 1, the Bluetooth dwell time data were used to calculate delay using Equation (3-11). For Method 2, the detection and travel times were used to calculate delay of each Bluetooth enabled vehicle using equation(3-15). The estimated individual vehicle delays were aggregated over 5-minute intervals to compute the estimated average control delay.

The Vissim traffic simulation is capable of reporting individual vehicle delay. Vissim calculates delay as follows:

$$d_{i,v} = tt_v^j - tt_{v,desired}^j \quad (3-17)$$

Where:

$tt_v^j$  : travel time of the  $v^{th}$  vehicle in segment  $j$

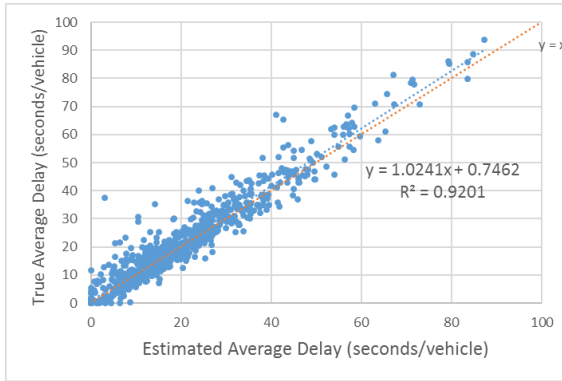
$tt_{v,desired}^j$  : desired travel time of  $v^{th}$  vehicle in segment  $j$

The desired travel time of each vehicle in a segment is the time it takes to travel that segment by its desired speed. The desired speed is a function of car following parameters, vehicle characteristics parameters, and some random behavior parameter. The delay, desired speed and desired travel time is calculated in simulation automatically. Average approach true delay was calculated by aggregating the individual vehicles delays over each 5-minute interval.

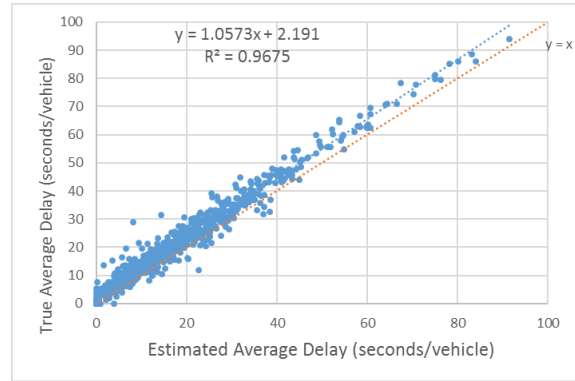
### 3.7.2 Results

Figure 3-12 shows the relationship between the average delay estimate using the proposed methods and the true delay.

### Queue < Effective Range

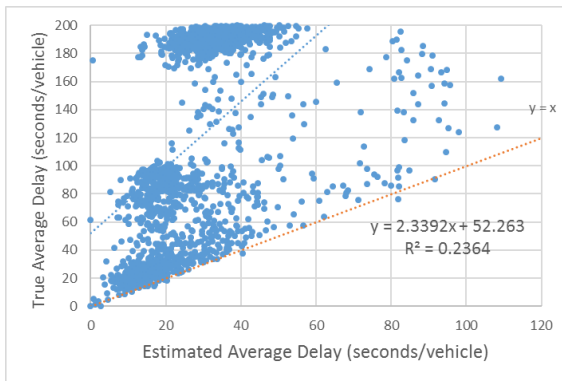


(a) Method 1

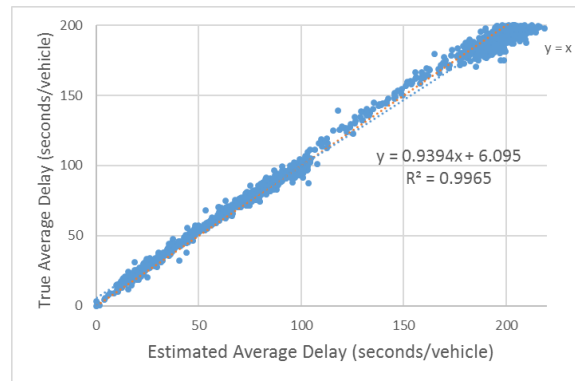


(b) Method 2

### Queue > Effective Range

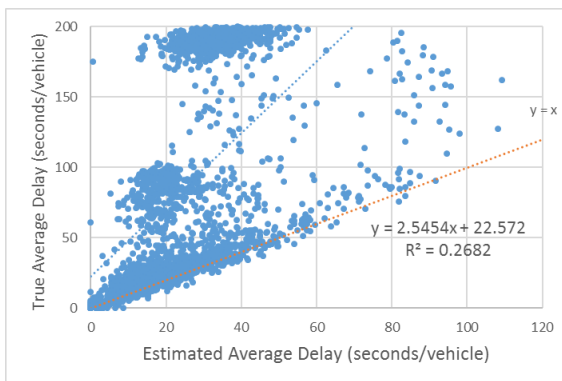


(c) Method 1

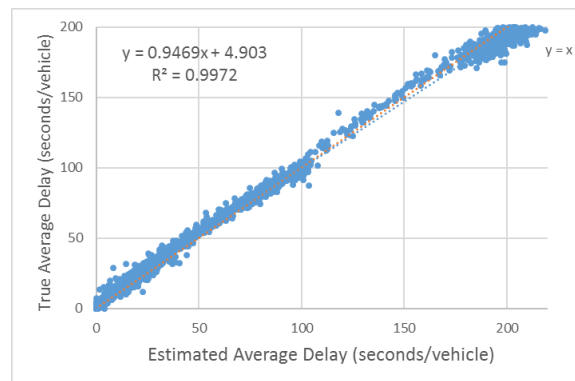


(d) Method 2

### All Cases Together



(e) Method 2



(f) Method 2

Figure 3-12: Simulation Results

The estimated average delay in Figure 3-12 (a, c, d) are calculated using Method 1 and the estimated average delay in Figure 3-12 (b, d, f) are calculated using Method 2.

The results for Method 1 show that when queues are less than the effective detection range, then Method provides a very accurate estimate of the true average delay. However, when queues extend beyond the effective detection range, the dwell times measured by the Bluetooth detector capture only a portion of the delay and the estimates from Method 1 contains substantial error.

In contrast, Method 2 provides high accuracy regardless of the length of the queues.

Table 3-2 tabulates the accuracy of the two proposed methods as a function of the maximum queue length. The accuracy of the two methods is quantified in terms of the Mean Absolute Error (MAE) and Mean Absolute Relative Error (MARE). MAE is more meaningful when the queue is less than 100m because in these cases the absolute values of delay are often quite small and estimation errors that are of no practical significance (e.g. 2 or 3 seconds) can result in very large relative errors.

Recall, that Method 1 is formulated with the assumption that all of the delay occurs within the effective detection zone. Given that we have modelled the detection radius as 100m, we expect Method 1 to be as accurate as Method 2 when the maximum queue length is less than 100m. This expectation is supported by the results. .

However, when the maximum queue length is greater than the effective detection range, Method 2 is substantially more accurate than Method 1 (the MAE of Method 2 is only 1/30<sup>th</sup> of the MAE of Method 1). When all cases are combined Method 2 remains substantially more accurate than Method 1 (MAE of Method 2 is approximately 1/20<sup>th</sup> of the MAE of Method 1).

Therefore, if in an intersection, we expect that the maximum queue length is less than the effective detection range Method 1 and Method 2 are both suitable. The advantage of using Method 1 is that this method requires only a single detector. On the other hand, if the expected queue length is more than the effective range or it is not possible to estimate the expected queue length, then Method 2 should be used and two detectors are required.

**Table 3-2: Evaluation of Proposed Methods using Simulation Data**

<i>Case</i>	<i># of Observations</i>	<i>Method 1</i>		<i>Method 2</i>	
		MAE (seconds)	MARE (%)	MAE (seconds)	MARE (%)
<i>Queue ≤ 100 meter</i>	813	2.9	20%	2.0	13%
<i>Queue &gt; 100 meter</i>	1820	89.3	64%	3.0	4%
<i>All Cases Together</i>	2633	62.7	50%	2.9	9%

### 3.8 Conclusions and Recommendations

Two methods have been developed to estimate control delay using data available from Bluetooth detectors. Method 1 requires data from a single Bluetooth detector deployed at the intersection and estimates delay on the basis of the measured Bluetooth dwell time. This model structure is similar to the model propose by Abbas et al (2013). This model has a high level of accuracy (MAE  $\approx$  3 seconds) when queue length is less than the effective range of the Bluetooth detectors but performs poorly when queues exceed the detector range (MAE  $\approx$  89 seconds).

Method 2 uses Bluetooth measured travel time to estimate control delay. This method requires data from two Bluetooth detectors, one at the intersection and one upstream (either at the next upstream signal controlled intersection or at a midblock location). This method can be used regardless of the length of queues and provides a high level of accuracy (MAE  $\approx$  3 seconds) both when queues are less than and greater than the effective range of the Bluetooth detector.

The overall results suggest that the proposed methods are suitable for estimation of intersection delay using Bluetooth detectors. The estimated delay can be used as the key measure of performance for an intersection in offline and in online applications. This could be the basis of advanced traffic management systems and advanced traveler information systems that rely on Bluetooth measurements. We also developed our simulation framework which can be combined with commercially available traffic microsimulation models to evaluate and develop the use of Bluetooth technology within ATMS.

# **Chapter 4**

## **Adaptive Green Split Optimization of Signalized Intersections Using Bluetooth Technology**

### **4.1 Introduction**

At grade intersections, typically form the capacity bottlenecks within urban road networks because at these locations, the capacity must be shared among competing traffic streams. At signalized intersections, the capacity is shared by cyclically allocating the right of way to different competing traffic streams through the use of traffic signal heads.

There are four main types of traffic signal controls, namely:

1. Fixed time control in which a signal timing plan is determined off-line on the basis of turning movement counts and then is implemented. Fixed time plans are typically updated every 3 to 5 years. Fixed time plans are typically determined for specific times of the days, such as the AM peak, mid-day, PM peak, and off-peak periods.
2. Actuated control in which sensors (usually a form of in-pavement detector) are deployed to measure the presence/passage of vehicles in a specific lane at a specific distance from the intersection stop line. The data from the sensors can be used to determine if the phase should be skipped or implemented and can be used to dynamically extend the green interval (up to a specific maximum) if vehicles are detected. Actuated control is most often used for dedicated left turn lanes to provide a protected left turn phase.
3. Traffic responsive control in which the information from traffic sensors are used to determine if it is advantageous to switch from the existing signal timing plan to some other, pre-defined, signal timing plan. A library of plans is developed and the selection of the optimal plan for the current conditions is done in real-time.



4. Traffic adaptive control in which information is obtained from traffic sensors to optimize the intersection operations in real-time by dynamically adjusting green interval durations, cycle length, offsets, and potentially phase schemes).

Various methods have been developed to optimize cyclic and acyclic adaptive signal control. In order to have a better understanding of Adaptive control systems, Table 4-1, summarizes the key characteristics of the well-known adaptive traffic control systems (ATCS) systems namely, SCOOT<sup>1</sup> (Hunt et al. 1981), SCATS<sup>2</sup> (Lowrie 1982), RHODES<sup>3</sup> (Mirchandani, Head 2001), OPAC<sup>4</sup> (Pooran, Farradyne 2000), and ACS-Lite<sup>5</sup>(Luyanda et al. 2003). For further information, the interested reader is referred to studies by (Stevanovic 2010, Curtis 2010, FHWA 2008) who provide a comprehensive review regarding the implementation of these ATSCs and detailed description about their operation.

**Table 4-1: Summary of major ATCS**

		SCOOT	SCATS	RHODES	OPAC	ACS-Lite
<b>Network Configuration</b>		Grid	Arterial	Arterial	Arterial	Arterial
<b>Location of Detectors<sup>1</sup></b>		SL, US	SL	SL, MB, US	SL, US	SL, UD
<b>Optimization<sup>2</sup></b>	Split	P	R	P	P	R
	Cycle	R	R	P	P	---
	Offset	P	R	P	P	P
<b>Split Control</b>		Central	Central	Central	Central	Local
<b>Initial Capital Cost (per intersection)</b>		\$30,000 to \$60,000	\$25,000 to \$30,000	\$30,000 to \$50,000	\$20,000 to \$50,000	\$8,000 to \$12,000
<b>Benefits<sup>3</sup></b>	Travel Time	-29% to -5%	-20% to 0%	-7% to +4%	-26% to +10%	-28% to +7%
	Delay	-28% to -2%	-19% to +3%	-19% to -2%	NA	-38% to +2%
	Stops	-32% to -17%	-24% to +5%	NA	-55% to 0%	-35% to -28%

Notes:

<sup>1</sup> SL = Stop Line; MB = Mid-Block; US = Upstream

<sup>2</sup> P = Proactive; R = Reactive

<sup>3</sup> negative values = reduction; positive value = increase; NA = Not available

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<sup>1</sup> Split Cycle Offset Optimization Technique

<sup>2</sup> Sydney Co-ordinated Adaptive Traffic System

<sup>3</sup> Real Time Hierarchical Optimized Distributed Effective System

<sup>4</sup> Optimized Policies for Adaptive Control

<sup>5</sup> Adaptive Control Software Lite

Regardless of the form of signal control that is used, intersection performance is usually quantified in the terms of average vehicle delay, stops, and queue length. Ironically, most existing signal control systems are not able to measure delay directly, so they estimate delay on the basis of measured vehicle counts using various types of models. These models introduce error in the delay estimation process and may contribute to sub-optimal operation of the intersection.

The first step in developing an adaptive traffic signal control system is to optimize the green split of an isolated intersection. If we are able to demonstrate reasonable performance in green split optimization using data from Bluetooth detectors, then we can move forward and develop other components of an adaptive system (e.g. offset optimization, network optimization). Therefore, in this chapter, we investigated an isolated intersection and proposed a green split optimization algorithm using control delay directly obtained from Bluetooth sensors. Several traffic scenarios have been tested using a custom-built simulation framework and the performance of the proposed optimization method has been evaluated. Furthermore, a sensitivity analysis was performed to estimate the optimal set of control parameters.

## **4.2 Bluetooth detectors and their application to transportation**

As mentioned in Chapter 3, previous studies have primarily examined the use of Bluetooth detectors to measure travel times of individual vehicles. However, it is possible to extract additional information from Bluetooth detections – specifically dwell time. This dwell time can be used to estimate the control delay experienced by vehicles performing different turning movements at signalized intersections.

To date there are few studies that have used Bluetooth data for estimating delay. Abbas et al. proposed two models to estimate control delay (one as a function of hits and the other a function of dwell time) on the basis of Bluetooth data (Abbas et al. 2013).

In Chapter 3, we proposed two methods (Method 1 and Method 2) to estimate control delay that extend and improve upon the models by Abbas et al. Method 1 is similar to the model proposed by Abbas et al and estimates control delay on the basis of dwell time from a single Bluetooth detector located at the intersection. This model has a high level of accuracy when queue lengths are less than the effective range of the Bluetooth detectors. Method 2 uses

Bluetooth measured travel time to estimate control delay. This method requires two Bluetooth detectors, but is substantially more accurate than Method 1, or the models by Abbas et al, especially when queue length is greater than the effective range of the Bluetooth detectors. In this chapter, we use Method 2 to estimate control delay.

### 4.3 Proposed Methodology

Figure 4-1 shows the proposed framework for using Bluetooth data for development of an adaptive traffic signal green split optimization. The main components of the proposed methodology are: (1) data processing; (2) estimation; (3) optimization; and (4) implementation.

The framework works on a rolling horizon. At the end of each time interval, data that were collected in real-time are processed in the Data Processing Module. The Estimation Module receives data from the Data Processing Module and generates the data required by the Optimization Module including estimates of movement delay and aggregated delay by movement group<sup>1</sup>.

The Optimization Module uses the available data to identify the most critical and least critical phase, and selects the appropriate green split adjustment in real-time. Then the Implementation Module applies the selected strategy.

This process happens continuously at the end of each time interval. The length of this time interval depends on the time of day. The selection of time interval is discussed in 4.3.1.

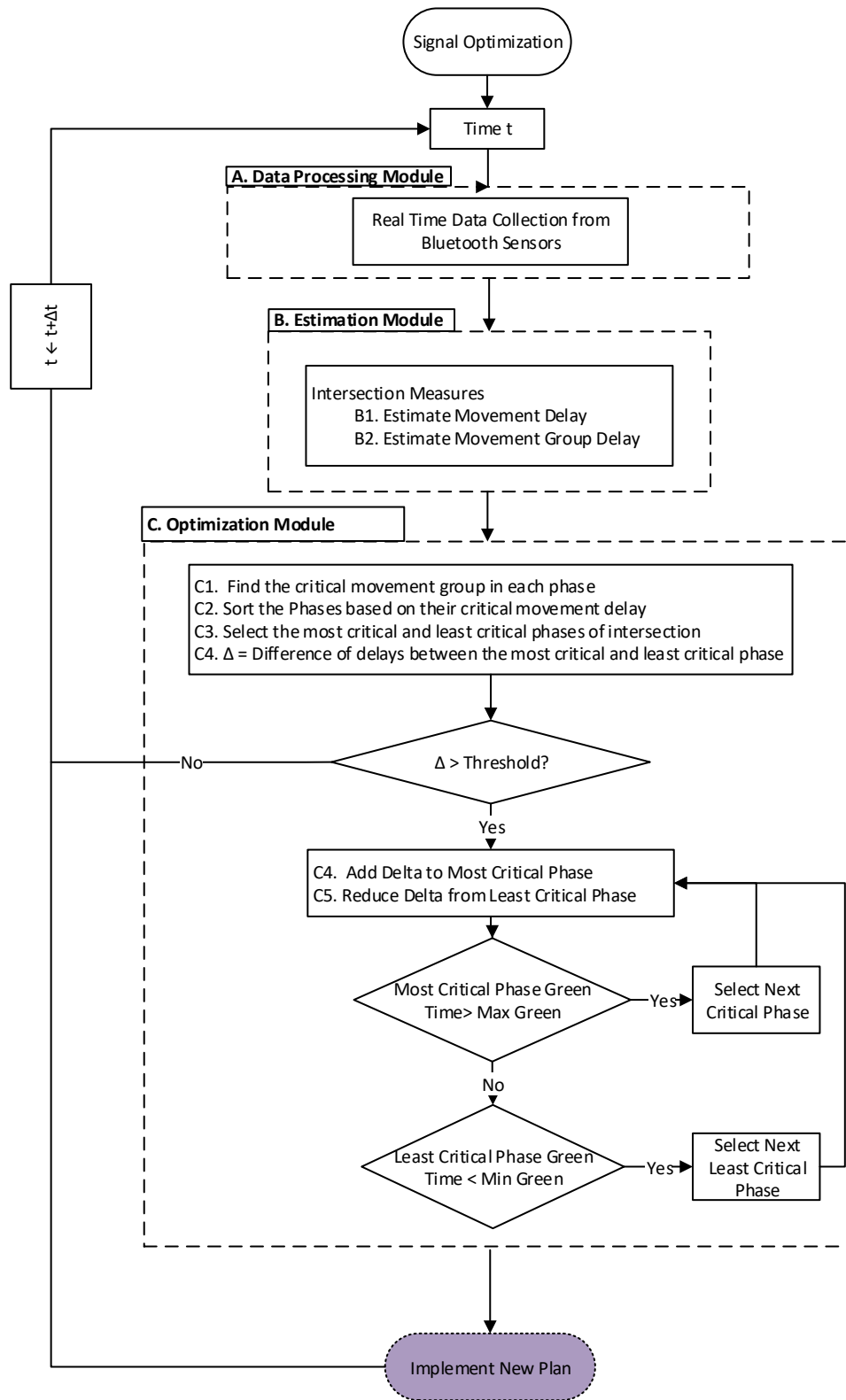
The estimation and optimization components are discussed in more detail in the following sections.

The proposed methodology is developed considering the following assumptions:

- Signal phases and cycle length are predefined and known.
- The detected Bluetooth equipped vehicles represent an unbiased sample of the population of vehicles in the traffic stream.

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<sup>1</sup> We call movements from each approach that discharge during the same phase a *movement group*.



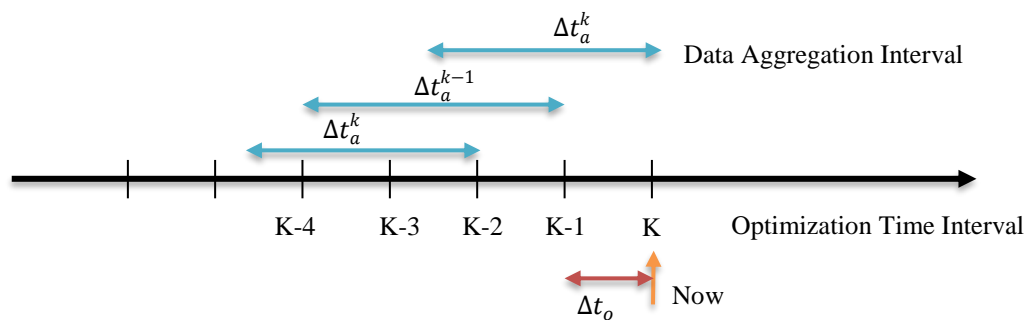
**Figure 4-1: Proposed framework for adaptive green split optimization**

- Signalized intersection timings are accessible in real-time and changes can be applied in real-time.
- The data obtained from Bluetooth detectors (including the detections and observed travel times) are accessible in real-time.
- Appropriate number of Bluetooth detectors are installed along the corridor and cross streets (the required number and location of detectors is described in Section 4.3.2).
- There is no spill back from the downstream intersections.

### 4.3.1 Time Intervals

The proposed methodology performs an optimization at fixed time intervals on the basis of data acquired by the system over the recent past. Two time intervals are critical in this system as illustrated in Figure 4-2.

- 1- **Optimization Time Interval ( $\Delta t_o$ ):** At the end of each Optimization Time Interval, the system performs the optimization calculations and updates the allocation of available green time to each phase. The value of ( $\Delta t_o$ ) may vary throughout the day. For example, during the peak periods,  $\Delta t_o$  may be set equal to 5 minutes and during off-peak periods it may be increased (15 minutes).



**Figure 4-2: Time Interval Diagram**

- 2- **Aggregation Time Interval ( $\Delta t_a$ ):** Each time the system performs an optimization, it compiles data (vehicle delays) representing recent traffic conditions. The length of time

over which these data are compiled is defined as the Aggregation Time Interval. At each optimization, the system uses all measured delay data during the associated aggregation time interval to calculate average delay of each movement group.

Our proposed method relies on estimates of average vehicle delay by movement group as an input to the optimization. The average vehicle delay is computed on the basis of delays estimated from the Bluetooth detector data for individual vehicles. The reliability of the estimated average delay is impacted by the number of individual vehicles that have been detected by the Bluetooth detectors (observations). As the aggregation time interval duration decreases, the number of observations will also decrease and become less than some minimum number of observations ( $N_{min}$ ) we determine are needed to have a sufficiently reliable estimate of the mean delay. On the other hand, if the length of aggregation time interval is too long, the data used for optimization of the intersection would be outdated. In both of these conditions, the performance of the algorithm will be negatively affected.

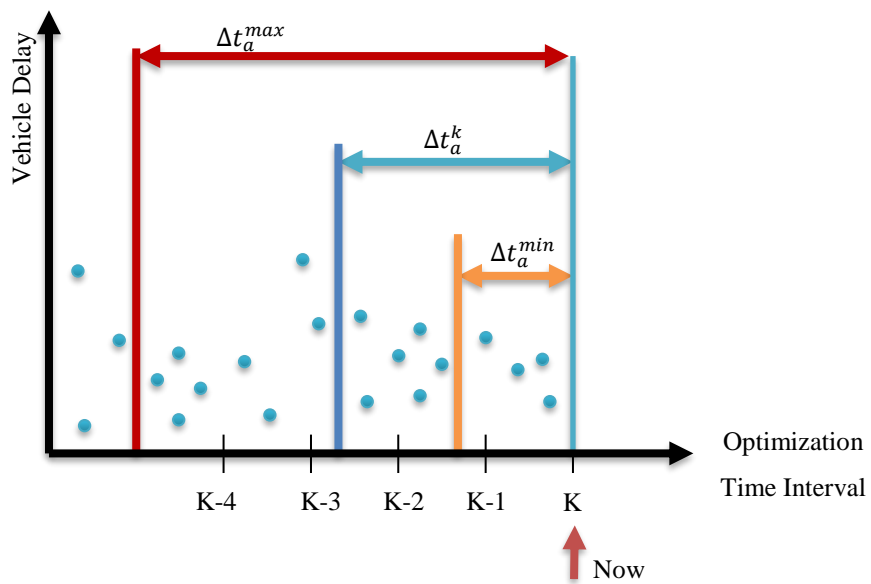
The number of observations acquired during a specific aggregation time interval duration is primarily a function of the traffic volume, level of market penetration of Bluetooth devices, and the traffic conditions. Given that all of these factors can change by location, time of day, day of week, etc., it is appropriate that  $\Delta t_a$  should be determined dynamically on the basis of the number of observations required.

We begin by defining a maximum and minimum value for  $\Delta t_a$  such that  $\Delta t_a^{min} \leq \Delta t_a \leq \Delta t_a^{max}$ . For a given optimization interval  $k$ , we set the aggregation time interval ( $\Delta t_a^k$ ) equal to the minimum threshold ( $\Delta t_a^{min}$ ). If the number of observed Bluetooth data for each movement group ( $N_{i,mg}$ ) is greater than  $N_{min}$ , then we will use a  $\Delta t_a^{min}$  as aggregation interval. If there is not enough observations, we extend the duration of the aggregation period ( $\Delta t_a^k$ ) just long enough until  $N_{i,mg} > N_{min}$  for all movement groups or until  $\Delta t_a^k = \Delta t_a^{max}$ .

If  $\Delta t_a^k = \Delta t_a^{max}$  and  $N_{i,mg} < N_{min}$  for at least one movement group, then the system cannot perform the optimization and the existing signal timing plan will be used until the

next update interval. If there are insufficient observations to permit optimization for an extended period of time, the system will switch to the predefined time of day plan.

Figure 4-3 illustrates the method described for aggregation time interval. The blue dots represent observations (delays obtained from individual vehicles). In this figure, we assumed that  $N_{min}=10$ . At optimization time interval  $k$ , there were only 4 observation during  $\Delta t_a^{min}$ . Therefore,  $\Delta t_a^k$  was incrementally increased until at least 10 observations were available.



**Figure 4-3: Illustration of aggregation Time Interval**

### 4.3.2 Configuration of Detectors

Bluetooth detectors typically use omni-directional antennas and therefore they are not able to identify the direction from which Bluetooth radio signals are being transmitted. Therefore, it is not possible to associate a specific MAC with a given turning movement using only the information collected by a single detector. However, distinguishing delays by turning movement (or equivalently by movement group) is an essential requirement for traffic signal control optimization.

Therefore, in order to capture the delay associated with different movements at each intersection and travel time of each segment, Bluetooth detectors must be installed at the intersection of interest and upstream on each approach. Given that the detection radius of a Bluetooth detector is approximately 100m it is necessary that the Bluetooth detectors be spaced a minimum of 200m apart. Typically, traffic signals along major arterial corridors are spaced between 400m and 800m apart and it is for these conditions for which the proposed model is most appropriate. Furthermore, the proposed method is based on the assumption that mid-block intersections/driveways may exist on the approach links between the Bluetooth detectors, but the traffic on the approach link is not subject to traffic signal or stop controls at these intersections (i.e. only the cross street or driveway would be controlled).

### 4.3.3 Estimation Module (B)

In Chapter 3, we developed a method to use Bluetooth data to estimate control delay. A brief description of the method is provided in this section and more details are available elsewhere (Chapter 3).

Figure 3-5 shows a time-space diagram of a hypothetical vehicle ( $v$ ) traversing segment  $j$  and performing a through movement at intersection  $i$  and then traversing segment  $j+1$ . Vehicle  $v$  encounters a queue. In this case, we define the delay as the difference between the travel time that this vehicle experiences over the segment  $j$  ( $tt_{ll,v}^j$ ) and its desired travel time over segment  $j$  ( $tt_{FFS}^j$ ) as follows:

$$tt_{ll,v}^j = t_{i,v}^l - t_{i+1,v}^l \quad (4-1)$$

$$d_{i,v} = \max(tt_{ll,v}^j - tt_{FFS}^j, 0) \quad (4-2)$$

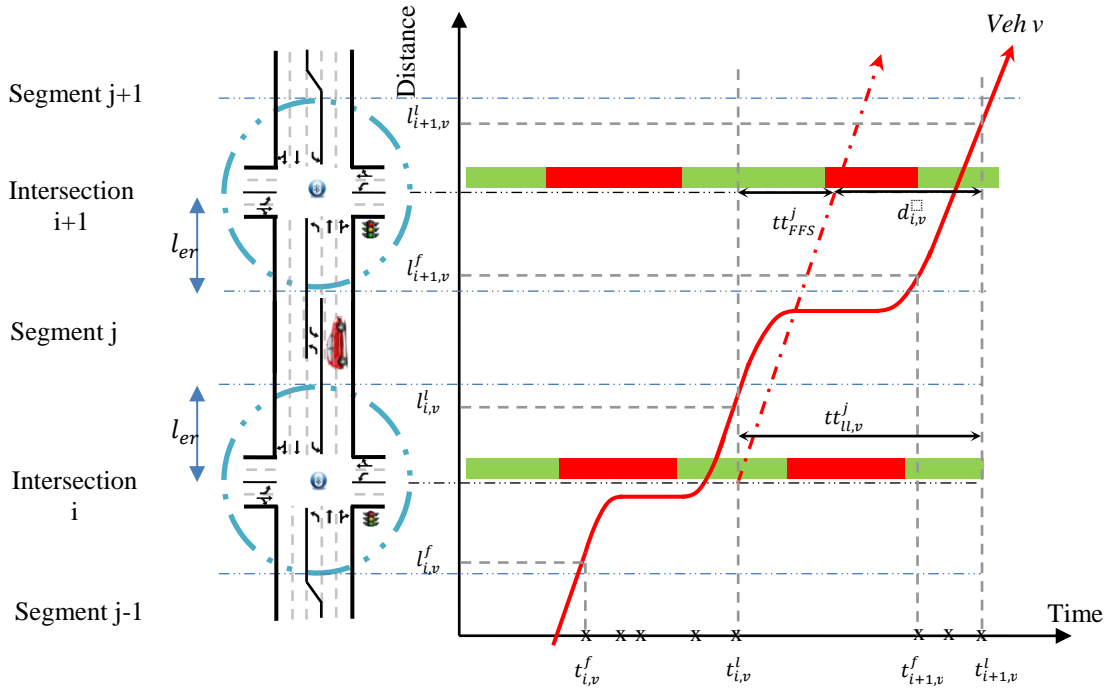
Where:

$t_{i,v}^l$  : Time of last detection of the  $v^{th}$  vehicle that passed intersection  $i$

$tt_{ll,v}^j$  : Travel time of the  $v^{th}$  vehicle in segment  $j$

$tt_{FFS}^j$  : Free flow travel time of vehicles over segment  $j$





**Figure 4-4: Bluetooth detection and sample trajectory of a vehicle when queue is greater than effective range**

If the free flow speed of the segment is unknown, a typical substitute would be to use the posted speed limit. Another method that we used in this chapter is to estimate the free flow travel time as the 15<sup>th</sup> percentile of the Bluetooth travel time for all vehicles that passed during the past set time period (e.g. hour). This method permits the free flow travel to be dynamically estimated in real time. This may be particularly valuable when free flow travel times are expected to change such as when adverse weather conditions exist.

Therefore, the average control delay of each movement group can be calculated as:

$$\bar{d}_{i,j,mg}^k = \frac{1}{n_{i,j,mg}^k} \sum_{v=1}^{n_{i,j,mg}^k} d_{i,v} \quad (4-3)$$

Where:

$\bar{d}_{i,j,mg}^k$  : Average delay of movement group  $mg$  in segment  $j$  at intersection  $i$  during time interval  $k$

$n_{i,j,mg}^k$  : Number of Bluetooth enabled vehicles from segment  $j$  which were in movement group  $mg$  at intersection  $i$  during time interval  $k$

In order to estimate vehicle delay using this method, we need to have an upstream Bluetooth detector at each approach. Figure 3-5 shows a sample configuration for this method. The upstream detector could be installed at the next upstream intersection or can be installed at a mid-block location. However, there should not be any signalized intersections between the upstream detector (intersection  $i$ ) and the downstream detector (intersection  $i+1$ ).

Equation (4-2) and (3-15) provides the opportunity to make a direct estimate of average vehicle delay for each movement group, rather than having to estimate delay on the basis of estimated traffic volumes. These estimates of delay are an essential input for offline or real-time traffic signal control optimization.

#### 4.3.4 Optimization Module (C)

Traditionally, green split optimization is described as a problem where the adjustable parameter is the green split (amount of green to allocate to each phase), and the objective is to minimize or maximize a measure of performance, normally average delay or a combination of delay and stops.

We can observe from this expression that delay is a function of  $X$ , the volume to capacity ratio, signal timing parameters (i.e. cycle length and green split), analysis time period, the initial queue (i.e.  $d_3$ ), and the degree of coordination (i.e.  $PF$ ).

As described in the previous chapter, it is possible to estimate the current average delay (i.e.  $d$  from Equation 3-6) on the basis of data obtained from the Bluetooth detectors. Therefore, it may appear possible to explicitly solve for optimal traffic signal control parameters (i.e. green splits, cycle length, and offsets) through the use of the HCM delay expression (Equation 3-6) and the average delay estimated from the Bluetooth detector data.

However, an examination of Equation 3-6 shows that in our applications, the progression factor  $PF$ , volume to capacity ratio  $X$ , and the size of the initial queue are all unknown. Thus there are more unknowns than equations and it is not possible to directly solve for the unknown

parameters. Furthermore, the HCM delay expression is developed to estimate average delay under steady-state conditions and not for real-time applications.

As a result, the proposed approach incrementally applies changes to the existing green time allocations in such a way as to equalize average delays on each approach.

As the Bluetooth technology provides us with the direct estimate of average intersection delay, we are able to distinguish the oversaturated and under saturated conditions. This provides us the opportunity to have a more robust algorithm for each condition.

### A. Under Saturated Condition

In this research, we propose a method similar to the HCM (2010). At the intersection during each time interval, we find the critical movement group (i.e. the movement group having the largest delay) in each phase. From this set of critical movement groups, we identify the critical movement group with the largest delay and the critical movement group with the smallest delay. If the difference between these two delays is greater than a threshold, then we reduce the green time allocated to the phase with the critical movement group having the smallest delay and increase the green time to the phase with the critical movement group with the largest delay.

The following algorithm describes the details of this green split optimization method. The selection of values for the model parameters and thresholds is discussed in Section 4.5.

**Step #1:** Find the critical movement group in each phase.

In each phase, the critical movement group is defined as the movement group which experiences the highest average delay:

$$\bar{d}_{i,cr}^{k,p} = \max(\{\bar{d}_{i,j,mg}^k \mid \forall m \in p\}) \quad (4-4)$$

Where:

$\bar{d}_{i,cr}^{k,p}$  : Delay of critical movement group of phase  $p$  at intersection  $i$  during time interval  $k$

**Step #2:** Find the most critical and least critical phases of intersection.

Sort the delays of critical movements of the phases. Choose the minimum and maximum values of delays as least-critical phase and most-critical phase:

$$\bar{d}_{i,mcr}^k = \max(\{\bar{d}_{i,cr}^{k,p} \mid \forall p \in P_i\}) \quad (4-5)$$

$$\bar{d}_{i,lcr}^k = \min(\{\bar{d}_{i,cr}^{k,p} \mid \forall p \in P_i\}) \quad (4-6)$$

$$\Delta d_i^k = \bar{d}_{i,mcr}^k - \bar{d}_{i,lcr}^k \quad (4-7)$$

Where:

$\bar{d}_{i,mcr}^k$  : Delay of most critical phase at intersection  $i$  during time interval  $k$

$\bar{d}_{i,lcr}^k$  : Delay of least critical phase at intersection  $i$  during time interval  $k$

$P$  : Collection of all phases at intersection  $i$

$\Delta d_i^k$  : Difference of delays of least-critical phase and most-critical phase at intersection  $i$  during time interval  $k$

If the difference of delays of least-critical phase and most-critical phase ( $\Delta d_i^k$ ) is greater than a threshold ( $\Delta_T$ ),  $\Delta d_i^k > \Delta_T$ , then we need to reduce the green interval of least-critical phase by  $g_\Delta$  and add it to the green interval of the most critical phase.

If, by reducing the green time from one phase, the green time will become less than the minimum required green interval for that phase (e.g. minimum required green for pedestrians), then the green time will be set to the minimum green. If it is already the minimum, the second lowest calculated critical phase will be chosen as the candidate for change and the same process will be executed.

If, by increasing the green time from one phase, the green time will become more than the maximum allowable green interval for that phase, then the green time will be set to the maximum green. If it is already the maximum, the second highest calculated critical phase will be chosen as the candidate for change and the same process will be executed.

The proposed optimization approach is not applicable to actuated protected left or right turn phases because it is not possible to perform individual vehicle actuations with Bluetooth detectors. Therefore, it is required to install a loop detector for detection of left or right turn requests. The Bluetooth system can adjust the maximum green of the protected phase in the

same method described in permissive lanes, if there are enough observations in each time interval.

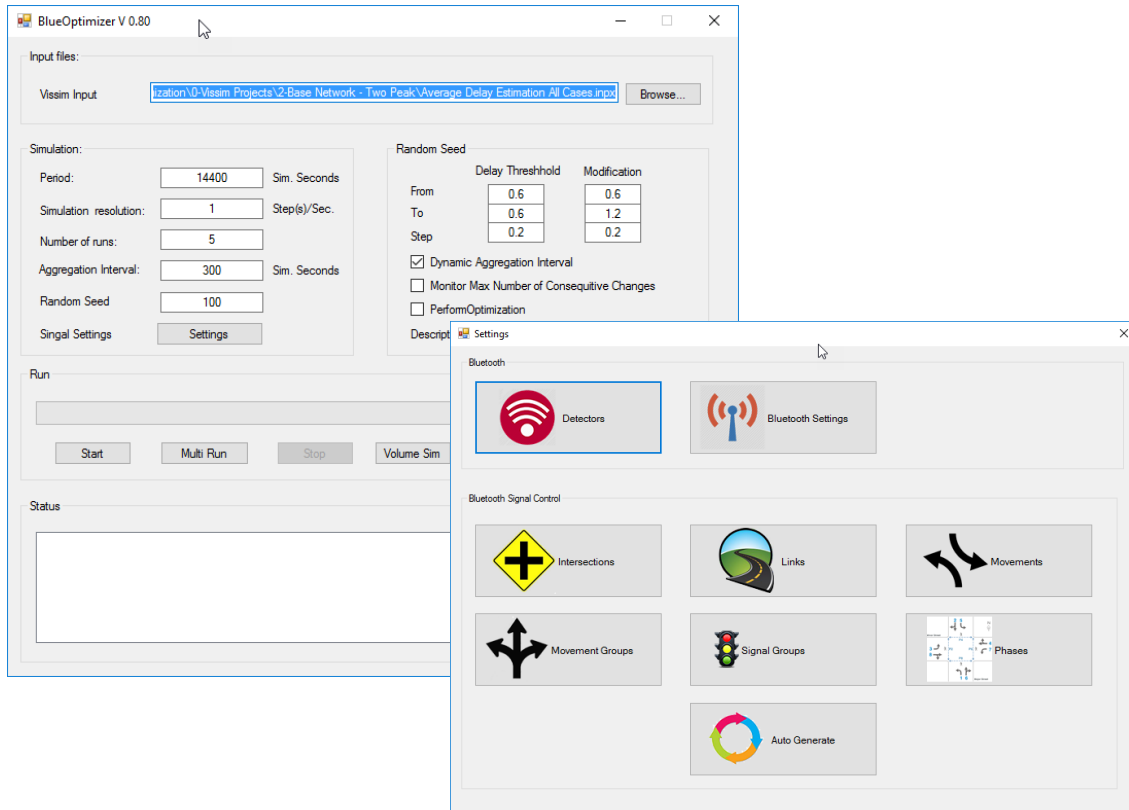
### **B. Oversaturated Condition**

When the average delay of all phases is greater than the level of service F delay value (80 seconds in HCM 2010), the system will switch to a predefined plan that has been optimized for over-saturated conditions.

## **4.4 Evaluation of Proposed Green-Split Optimization Methodology**

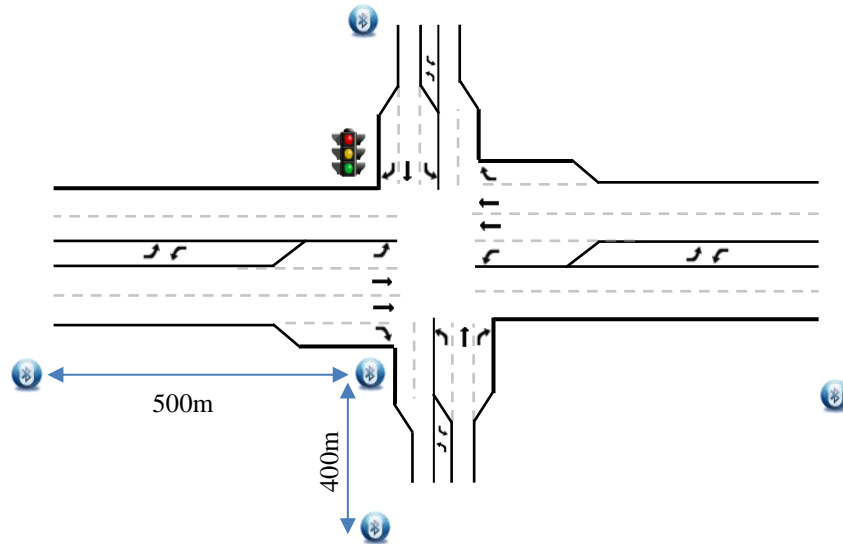
We have evaluated the proposed method using simulation as a precursor for a field evaluation. The use of simulation makes it feasible to evaluate the proposed method over a large range of traffic conditions; permits the direct collection of measures of performance such as travel time, delay, and stops; and enables direct comparisons to other traffic signal control methods for the same traffic conditions. In this chapter, we used the developed Bluetooth simulation framework (BlueSynthesizer) to synthesize Bluetooth detections.

In order to implement the proposed green split optimization algorithm, an optimization framework, *BlueOptimizer*, was developed. The framework enables us to define the objects required for optimization such as Bluetooth detectors, movements, movement groups, phases, signal controllers and associated Vissim simulation objects. The optimization framework takes control of the Vissim traffic simulation, replaces the signal controllers of Vissim and changes traffic signal heads directly. It also simulates the Bluetooth detection in real time along with simulation of traffic by Vissim. At each update interval, it estimates the delay experienced by individual vehicles (those measured by the Bluetooth detectors), movement group delay, and phase delay. Then it optimizes the green split according to the proposed method and updates the traffic signal timing plans for implementation in Vissim for the next time interval. Figure 4-5 shows a screenshot of the developed software.



**Figure 4-5: Screenshot of BlueOptimizer**

For the purpose of evaluation of the proposed methodology, an isolated intersection with a typical approach geometry was simulated (Figure 4-6). The northbound-southbound street (NB-SB) is a two-lane street and the Bluetooth detectors were located 400 meters upstream of the intersection on these approaches. The eastbound-westbound street (EB-WB) is a four-lane street and the Bluetooth detectors were located 500 meters upstream of the intersection on these approaches. Each approach consists of dedicated left turn, though, and right turn lanes. The left turn and right turn bays are 75m long.



**Figure 4-6: Layout of Intersection**

Figure 4-7 presents the structure of the signal timing phases and Table 4-2 shows the green split parameters for each phase. The fixed time signal plan was optimized using Vissim simulation software and it is the default green split at the start of simulation. The minimum green time is estimated from the time required for pedestrians.



**Figure 4-7: Signal Timing Phase Structure**

**Table 4-2: Phase Configuration**

Phase	Description	Fixed Green (s)	Min Green (s)	Max Green (s)	Amber (s)	All Red (s)
Phase 1	Protected LT EB and WB	15	10	25	3	2
Phase 2	Permissive EB and WB	35	20	50	3	2
Phase 3	Permissive NB and SB	35	20	50	3	2

The duration of simulation is 14,400 seconds (48 five-minute time intervals). The first 900 seconds is allocated for warm up. The signal controller starts to collect Bluetooth delay information after 900 seconds. After 15 minutes of data collection, the optimization starts at time 1800 seconds (time interval 6). In this simulation, we set  $g_{\Delta}$  to 5 seconds and  $\Delta_T$  to 9 seconds. We assumed the level of market penetration (LMP) for Bluetooth devices is 10%. We set the minimum required number of observation ( $N_{min}$ ) equal to 10. The optimization time interval ( $\Delta t_o$ ) was set to 5 minutes. The minimum data aggregation interval duration ( $\Delta t_a^{min}$ ) was set equal to 5 minutes and the maximum data aggregation interval duration ( $\Delta t_a^{max}$ ) was set equal to 15 minutes. Furthermore, we used a simplified rule for incrementally increasing the duration of  $\Delta t_a^k$ . If there were insufficient number of observations in 5 minutes, we increased the duration of  $\Delta t_a^k$  to 15 minutes.

The traffic demand on each approach varies over time as illustrated in Figure 4-8 (a). The volume pattern has three peaks: (1) EB-WB peak; (2): NB-SB peak, (3): the peak in both streets. This pattern can be a good representative of real world situations where we have increase in one direction or both at the same time. The turning ratio for the right turn and left turn in all approaches are 10% during the entire simulation.

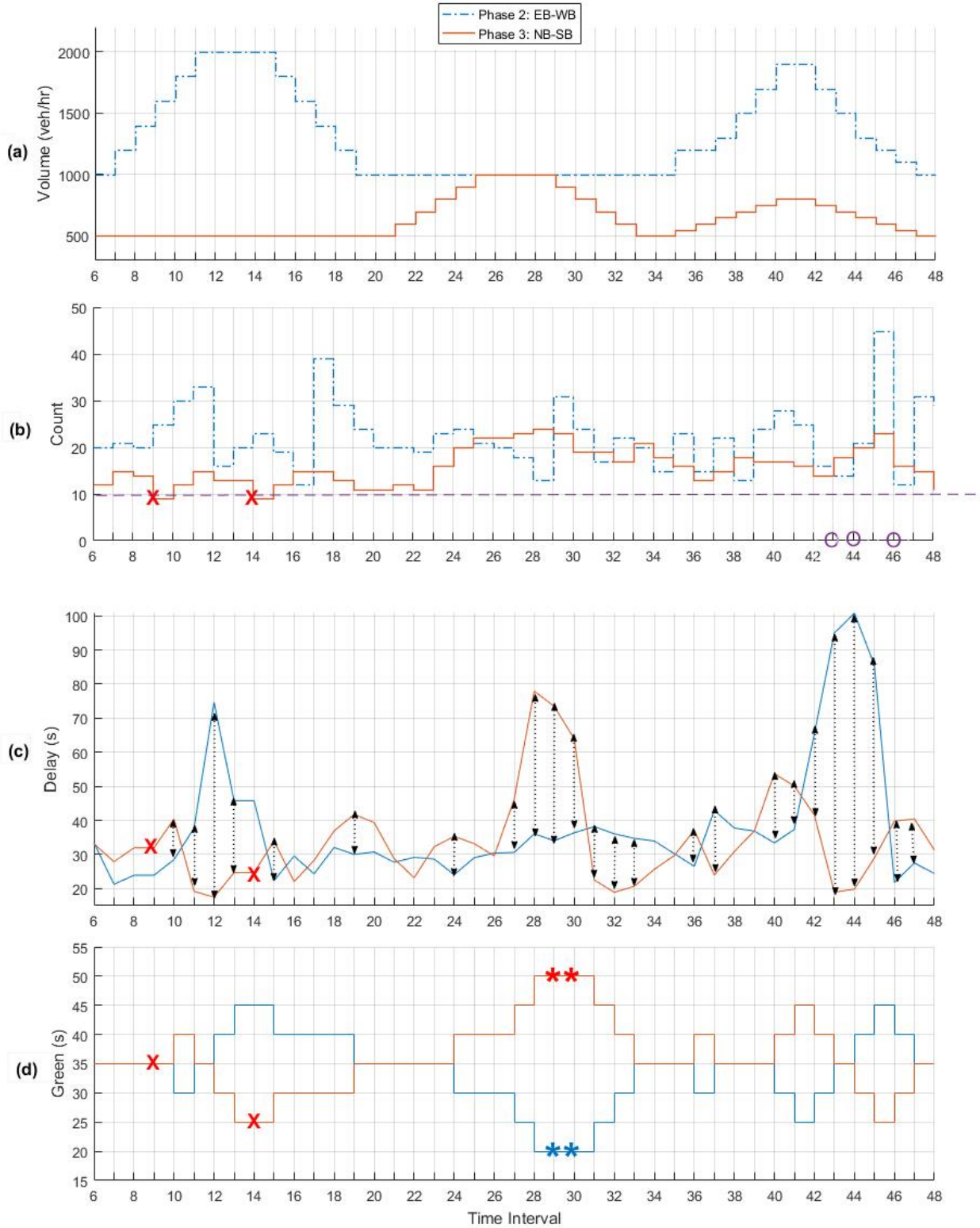
Figure 4-8 (b) shows the number of Bluetooth observations available during each optimization interval for the critical movement group of each phase. The intervals marked with a red "X" (time intervals 9 and 14) are intervals in which  $\Delta t_a^k = 15$  minutes and the number of observations was still less than 10. Consequently, for these intervals, no optimization was possible.



The time intervals marked with the “O” (time intervals 43, 44, and 46) are intervals for which there were sufficient number of observations when  $\Delta t_a^k = 5$  minutes. For all the other intervals,  $\Delta t_a^k$  was increased to 15 minutes to reach the minimum number of observations.

Figure 4-8 (c) shows the estimated phase delay from Bluetooth detections for phase 2 and 3. When the difference is greater than the  $\Delta_T$ , an arrow indicates the difference. At these time intervals, the difference in delays is sufficiently large to justify reallocating the green times. Figure 4-8 (d) shows the result of optimization, which is the implemented green split. If the green time of a phase reached the maximum or the minimum green, it is marked with “\*” (time interval 29 and 30) and therefore the green split was not modified.

The temporally varying traffic demands represent three distinct peaks. The first reflects a peak in demands on the EB and WB approaches and occurs during time intervals 6 to 20. As the traffic demand increases, the delay on these approaches also increases (Figure 4-8 (c)). In response, the proposed green split optimization algorithm increases the green time of phase 2 (EB-WB phase) by reducing the green time of phase 3 (NB-SB phase). After this gradual reallocation of green time, the delay of EB-WB phase starts to decrease in time interval 13. As the volume starts to decrease at time interval 15, the system automatically adjusts the green split and returns to the original green split at the end of the peak (time interval 19).



**Figure 4-8: Illustrative sample of simulation data**

During the second peak (NB-SB peak), time interval 23 to 33, the system increases the green time allocated to phase 3 and reduces it from phase 2 until it reaches the maximum green time for this phase in time interval 29 and 30. As the delay decreases afterward, the system starts to adjust the allocation of green split and it reaches back to its initial plan at the end of the peak (time interval 33).

In the third peak, time interval 35 to 47, at the beginning the delay in NB-SB starts to increase and the system adjusts the green time allocation. Then the delay in EB-WB starts to increase in time interval 42 and the system increases the green time for this phase. At time interval 46, the delay in NB-SB increases and therefore, the system increases the green time allocated to phase 3. At the end, the system automatically adjusts the green split allocation and reaches to its initial plan at time interval 47.

#### 4.5 Parameter Selection

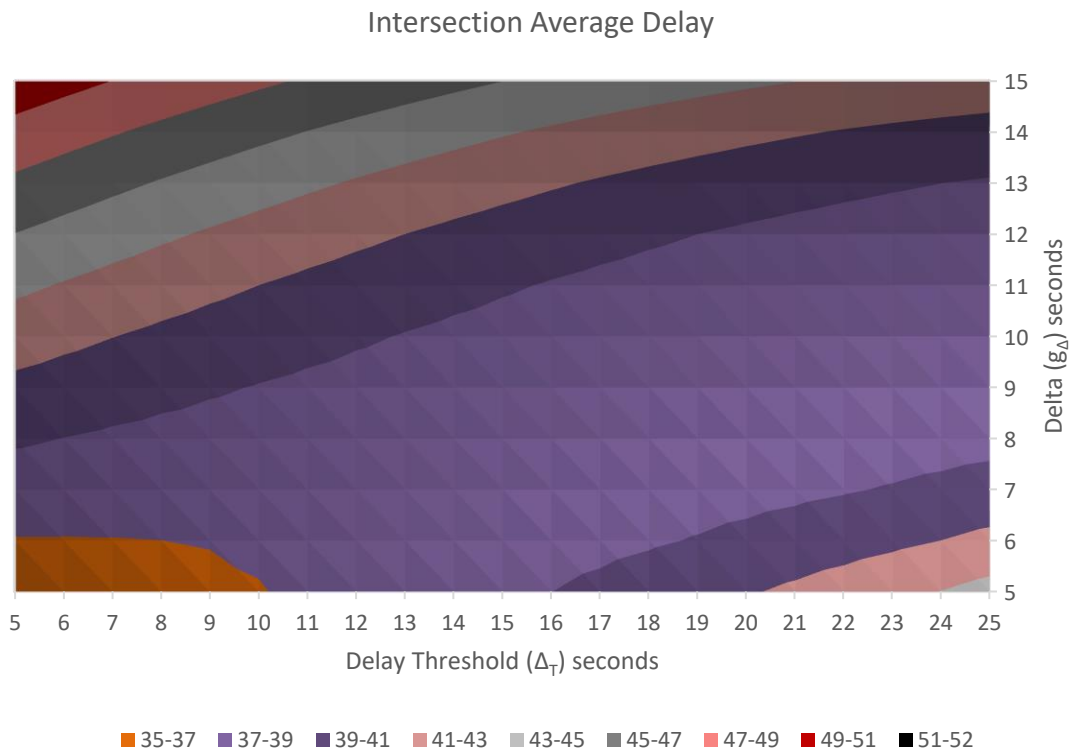
In order to estimate the optimal values of  $g_{\Delta}$  and  $\Delta_T$ , a sensitivity analysis was performed. The objective was to find set(s) of  $g_{\Delta}$  and  $\Delta_T$  that will result in the minimum average intersection delay as computed over the entire simulation. Therefore, the performance of the proposed optimization algorithm was evaluated on the isolated intersection using all possible combinations of  $g_{\Delta}$  and  $\Delta_T$ .  $\Delta_T$  varied from 5 to 25 seconds (in 1 second increments) and  $g_{\Delta}$  was varied from 5 to 15 seconds (in 1 second increments). Each combination was simulated three times, each time with a different random seed. There a total of  $21 \times 11 \times 3 = 693$  simulations were executed. For each intersection, the intersection average vehicle delay was computed considering the delay experienced by all vehicles after the warmup period (0 – 900 seconds) and on all four approaches.

A polynomial regression was calibrated to the data in which the intersection average vehicle delay ( $D$ ) was the dependent variable, and  $g_{\Delta}$  and  $\Delta_T$  were the independent variables. The interaction terms were also considered and only terms that were statistically significant at the 95% level were kept in the model. The final model was

$$D = 26.28 + 1.11\Delta_T + 1.83g_{\Delta} + .012\Delta_T^2 - .26\Delta_T g_{\Delta} + .009\Delta_T g_{\Delta}^2 \quad (4-8)$$

Figure 4-9 plots the relationship between  $g_{\Delta}$  and  $\Delta_T$  as described by the regression model and shows that the minimum value for average delay is achieved for smaller values of  $\Delta_T$  and

smaller values of  $g_{\Delta}$  (the green area of surface in Figure 4-9). As a result, there are several combinations of  $\Delta_T$  and  $g_{\Delta}$  that provide essentially same values of delay. When  $g_{\Delta}$  is set to five seconds,  $\Delta_T$  can be set any value from five to ten seconds. When  $g_{\Delta}$  is set to six seconds,  $\Delta_T$  can be set to any value from five to eight seconds. We set  $g_{\Delta}$  to five seconds and  $\Delta_T$  to nine seconds as our combination in this chapter.



**Figure 4-9: Average intersection delay as a function of the model parameters  $\Delta_T$  and  $g_{\Delta}$ .**

## 4.6 Results

In order to evaluate the performance of proposed methodology, the intersection in the simulation section was simulated with three different types of traffic signal control strategies, namely: (1) fixed time plans which were determined using the Vissim simulation software; (2) fully actuated control using the actuated controller logic built-in to Vissim; and (3) proposed green split optimization. Both the actuated control and the green split optimization control strategies begin with same traffic signal timings as the fixed time plan and the optimization parameters such as minimum and maximum green time of each phase were the same.

The traffic demands shown in Figure 4-8 (a) were considered as the base demands. The performance of the proposed green split optimization method was evaluated across a range of traffic conditions by multiplying the base demands by a one of four traffic demand factors (0.6, .08, 1.0, and 1.2). This factor was applied independently to the traffic demands on the northbound-southbound direction and eastbound-westbound direction. Each of the 16 traffic demand conditions were simulated 5 times, each time with a different random seed for each of the three traffic signal control strategies (240 simulations in total). The average intersection delay of each simulation was extracted as and averaged across the five replications as the measure of performance.

Table 4-3 shows the resulting average intersection vehicle delay for each of the three signal control methods for each of the 16 demand combinations. For each combination, we computed the difference in the mean intersection vehicle delay between the proposed green split optimization strategy and each of the conventional strategies (i.e. fixed time and actuated). Using the t-test we determined if the difference in means was statistically significant at the 95% confidence level. If the difference was statistically significant, we report the associated relative change in delay (positive is a reduction in delay). If the mean delays were not statistically different, then we have reported "Equal" in the cell.

**Table 4-3: Performance of the proposed method (average vehicle delay)**

		WB-EB												
		Method	0.6			0.8			1.0			1.2		
			Delay	BT	Imp <sup>1</sup>	Delay	BT	Imp	Delay	BT	Imp	Delay	BT	Imp
NB-SB	0.6	F-Act.	21.76	23.59	Inc	21.86	24.37	Inc	30.77	26.76	13%	46.65	36.24	22%
		Fixed	25.51		8%	27.32		11%	42.95		38%	83.43		57%
	0.8	F-Act.	24.17	23.63	Eq	23.86	24.58	Eq	33.77	27.20	19%	53.48	39.86	25%
		Fixed	28.37		17%	29.55		17%	43.78		38%	81.62		51%
	1.0	F-Act.	40.40	30.36	25%	39.48	33.27	16%	47.13	38.13	19%	77.60	52.81	32%
		Fixed	61.72		51%	57.83		42%	66.95		43%	100.11		47%
	1.2	F-Act.	74.80	39.86	47%	67.61	44.50	34%	75.56	58.39	23%	105.09	78.43	25%
		Fixed	86.61		54%	78.90		44%	85.22		31%	115.34		32%

Notes:

<sup>1</sup> Imp = Improvement; Eq = Equal; Inc = Increased.

From the results, we can observe that the actuated control strategy performs better than the fixed time strategy. This result is expected. We also observe that for all conditions tested, the proposed signal control strategy performs better than the fixed-time strategy and provides reductions in average delay that range from 8% to 54% depending on the traffic demands. Furthermore, for most of the conditions tested, the proposed strategy performs better than the fully actuated strategy and provides reductions in delay ranging from 13% to 47%. When the traffic demands are very low (i.e. 60% of base values), the proposed strategy does not provide improvements relative to actuated control. This is because when the volume is very low, there are relatively few observations (i.e. detected Bluetooth equipped vehicles). We set the minimum number of observations required equal to 10 and when fewer than 10 observations are obtained, no optimization is possible (the existing green split is used for the next time interval). Assuming 10% LMP, then when the traffic demand is less than 400 vph in each direction, on average we expect to detect 10 or fewer vehicles in a 15-minute interval and therefore in these intervals, we do not carry out any green time reallocation.

## 4.7 Conclusions and Recommendations

In this chapter, we proposed a method to optimize green splits at an isolated intersection using control delay obtained from Bluetooth detector data. The proposed method has been evaluated for a range of traffic demands using a custom-built simulation framework. Furthermore, a sensitivity analysis was performed to estimate the optimal set of control parameters.

The proposed method can provide up to 50% reduction in average delay in comparison with fixed signal timing and fully actuated controller. When the traffic volumes are very low, the proposed method does not provide improved performance because there are insufficient number of vehicle detected to provide reliable estimates of control delay. We also expect that the level of improvement expected in a field deployment can vary because of outliers, possible spillbacks from the downstream intersection, and rapid variations of traffic demands.

The overall results suggest that the proposed method is able to optimize the green split intersection, reduce intersection delay and improve level of service using only data obtained from Bluetooth detectors. There is no need for the installation of loop detectors or other dedicated traffic sensors for through movements. Traffic sensors are still required for dedicated turning lanes when those lanes are controlled by special phases (e.g. actuation for a protected left turn phase).

Green split optimization is the first step in developing a complete adaptive traffic signal control system for a corridor or network.

# Chapter 5 Adaptive Offset Optimization of Signalized Intersections Using Bluetooth Technology

## 5.1 Introduction

Offset is a parameter of the traffic signal timing plan and indicates the time difference between the start-time of green interval of the first phase of the signal timing plan at a given intersection and the start of the first phase at some reference intersection (this reference intersection is typically designated as the *master* signal).

The selection of the offsets in traffic signal coordination is critical for establishing vehicle progression. Figure 2-1 illustrates the effect of offset on vehicle delay. Figure 2-1a represents poor coordination and Figure 2-1b represents good coordination. The traffic volume, distribution of vehicle arrival times, the cycle length, and the green splits are the same for both conditions. The only difference is the offset (i.e. the start of the cycle at the downstream signal relative to the start time at the upstream signal).

The main inputs to the offset optimization process are: time to travel the segment between consecutive intersections, desired travel time<sup>1</sup>, and distance between intersections. The optimal coordination is achieved when the platoon arrives at the downstream intersection while the signal at the downstream intersection is green and any initial queue has been served. Therefore offset can be computed as the time required for the platoon to traverse the segment (Equation (5-1)).

$$O_{i+1,j} = \tilde{t}_j \tag{5-1}$$

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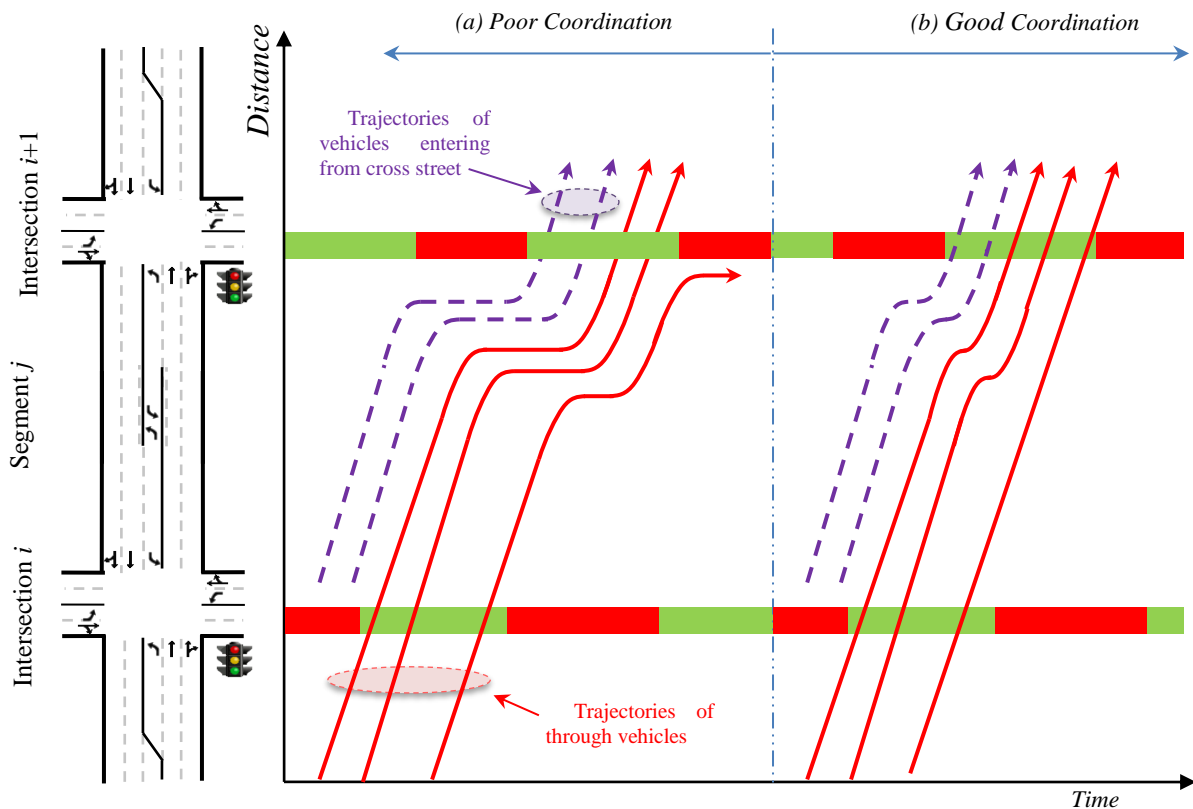
<sup>1</sup> Desired travel time is the time required for the platoon to travel from the upstream intersection to the downstream intersection when there is no delay incurred at the downstream intersection



Where  $O_{i+1,j}$  is the offset of the intersection  $i+1$  over segment  $j$ , and  $\tilde{t}_j$  is the desired travel time for the platoon over segment  $j$ . If the calculated value is greater than the cycle length, then the offset is computed as:

$$O_{i+1,j} = \text{mod}(\tilde{t}_j, c) \quad (5-2)$$

Where  $c$  is the cycle length (seconds).

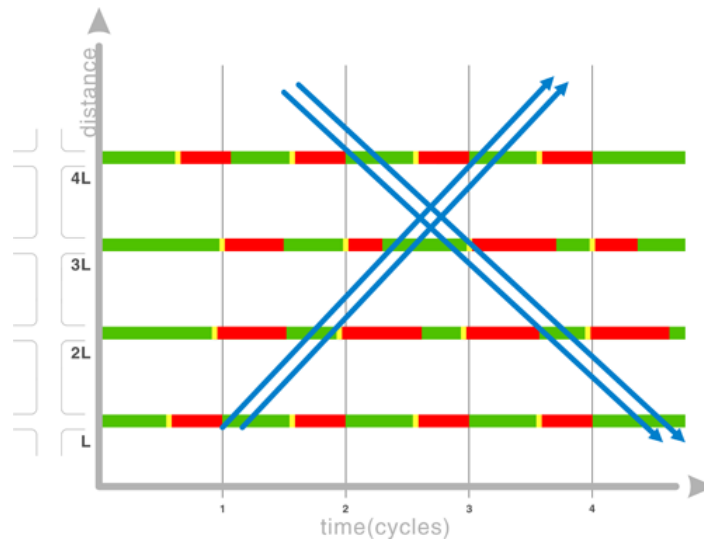


**Figure 5-1: The effect of coordination on vehicle delay**

Traditionally  $\tilde{t}_j$  is determined through field observation. In the absence of field data, some agencies compute the travel time assuming vehicles travel at the posted speed limit.

Once a candidate set of signal timings (including offsets) has been developed, the quality of the progression can be estimated using a space-time diagram as illustrated in Figure 5-2. The blue vectors in the diagram indicate the first and last vehicle departing from the upstream signal in a given cycle which are able to pass through all downstream intersections during the green

without delays. The difference in time between the departure of the last and first vehicle is defined as the green band.



**Figure 5-2: Time-Space Diagram of a Coordinated Timing Plan (FHWA 2008)**

Once the candidate set of signal timings has been refined using the space-time diagram, the timings are typically implemented and evaluated using field observations, typically obtained by driving a dedicated vehicle equipped with a GPS data logger along the corridor. Given the time and effort to collect these data, it is typical to collect a relatively small number of observations (5-10) over only a few days (2-3), significantly limiting the range of conditions over which the signal timing is evaluated.

On the other hand, these offline optimized fixed offsets cannot adapt to changes in desired travel time which may happen as a result of inclement weather, incidents, impedance due to parking manoeuvres, etc.

Most of current advance traffic management system discussed in Chapter 4 (Table 4-1) typically estimate offset using loop detector data. All these algorithms that rely on the loop detector data are not able to provide a direct estimate of the desired travel time. Therefore, there is a need for a system that can provide direct measurement of travel time and adjust offset in real-time dynamically.

In recent years, new technologies such as connected vehicle, license plate reading cameras, and Bluetooth detectors provide us with the opportunity to directly measure travel time and optimize the offset in real-time (Day, Bullock 2016, Goodall, Smith & Park 2013).

## **5.2 Bluetooth Detectors and Their Application in Offset Optimization**

In recent years, there are two major study in offset optimization. Day and Haseman (2010) developed a visual method for off-line assessment of progression on arterials on the basis of Bluetooth measurements. Essentially, they collected before data using Bluetooth detectors, examine the patterns to suggest changes to the offset and then collect data after the new offsets have been implemented in order to evaluate changes in quality of progression. Park and Haghani (2014) also proposed a method for offline optimization of signal offset using travel time and applied the optimized offset in a corridor.

To date, previous studies have primarily utilized Bluetooth detectors to use measured travel time in offline offset optimization. However, it is possible to perform real-time offset optimization using Bluetooth technology such that the offsets can adapt to changes in desired travel time in real-time.

In this chapter, we propose a method that can dynamically estimate the desired travel time on a sample of travel times collected by Bluetooth detectors and optimize the offset in real time.

## **5.3 Proposed Methodology**

Figure 4-1 shows the proposed framework for using Bluetooth data for development of an adaptive traffic signal offset optimization. The main components of the proposed methodology are: (1) data processing; (2) estimation; (3) optimization; and (4) implementation.

The framework works on a rolling horizon. At the end of each time interval, data which was collected in real-time is processed in the Data Processing Module. The Estimation Module receives data from the Data Processing Module and generates the data required by the Optimization Module including estimates of desired travel time.

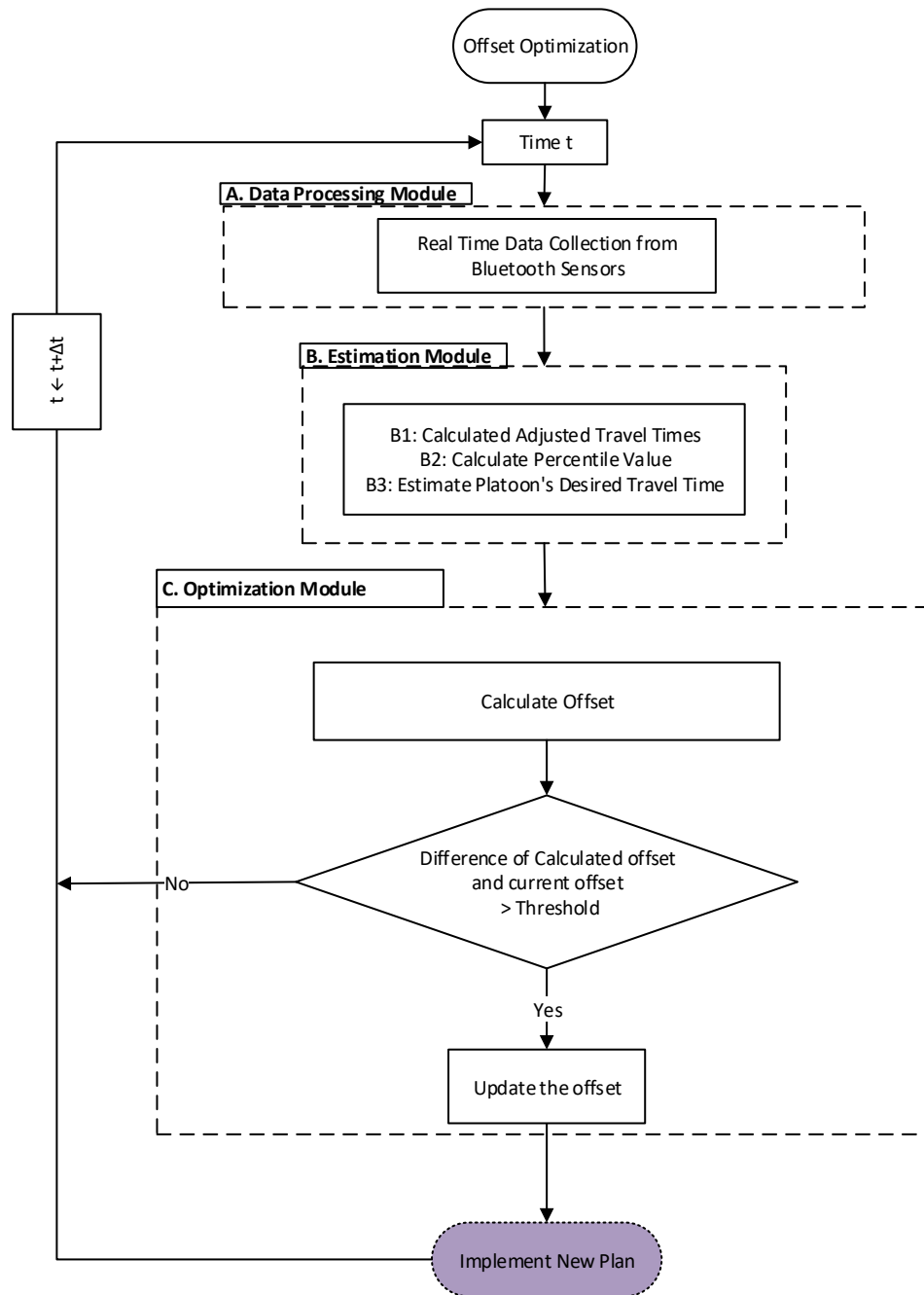
The Optimization Module uses the available data to identify the changes in the desired travel time, and selects the appropriate offset adjustment in real-time. Then the Implementation Module applies the selected offset.

This process occurs at the end of each time interval. The length of this time interval depends on the time of day. The selection of time interval is similar to Chapter 4 (section 4.3.1).

The estimation and optimization components are discussed in more detail in the following sections.

The proposed methodology is developed considering the following assumptions:

- Signal phases and cycle length are predefined and known.
- Direction of coordination in the corridor is predefined.
- The detected Bluetooth equipped vehicles represent an unbiased sample of the population of vehicles in the traffic stream.
- Signalized intersection timings are accessible in real-time and changes can be applied in real-time.
- The data obtained from Bluetooth detectors (including the detections and observed travel times) are accessible in real-time.
- Appropriate number of Bluetooth detectors are installed at each intersection along the corridor (the required number and location of detectors is described in Section 5.3.1).



**Figure 5-3: Proposed framework for adaptive offset optimization**

### 5.3.1 Configuration of Detectors

Given that the detection radius of a Bluetooth detector is approximately 100m it is necessary that the Bluetooth detectors be spaced a minimum of 200m apart. Typically, traffic signals

along major arterial corridors are spaced between 400m and 800m apart and it is for these conditions for which the proposed model is most appropriate. Furthermore, the proposed method is based on the assumption that mid-block intersections/driveways may exist on the approach links between the Bluetooth detectors, but the traffic on the approach link is not subject to traffic signal or stop controls at these intersections (i.e. only the cross street or driveway would be controlled).

### 5.3.2 Estimation Module (B)

The selection of the offsets in traffic signal coordination is critical for establishing vehicle progression. As discussed in the introduction section, the offset can be estimated according to the following equation:

$$O_{i+1,j}^k = \text{mod}(\tilde{t}_j^k, c) \quad (5-3)$$

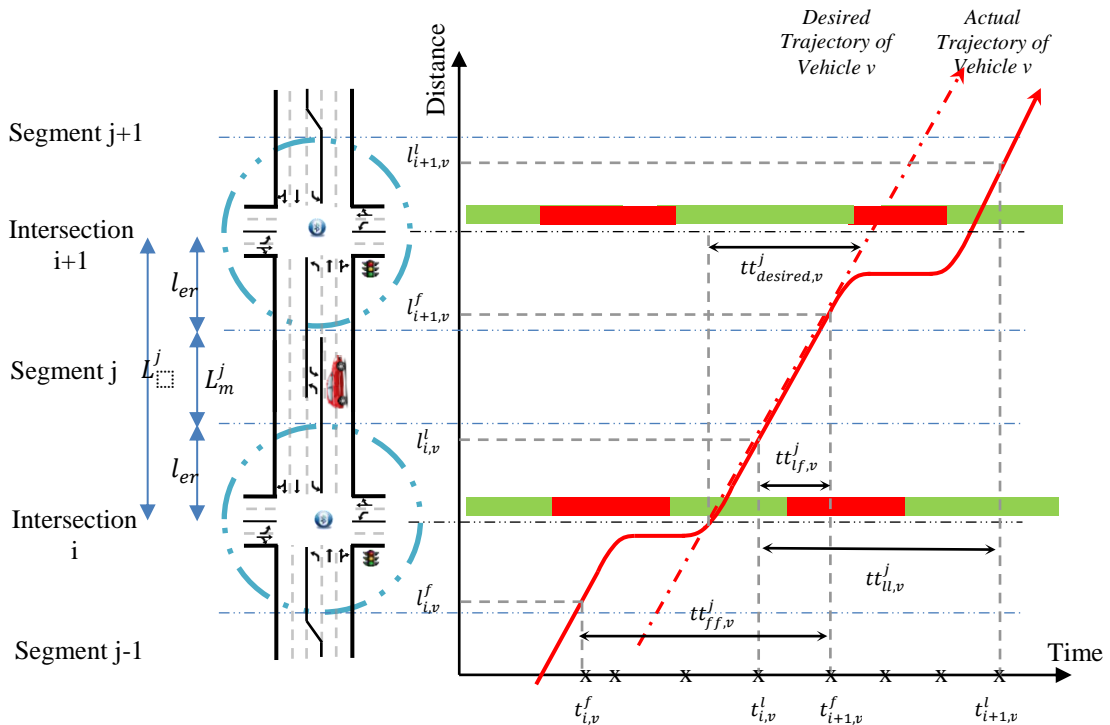
Therefore, in order to estimate the offset, we need to estimate the time required for the platoon to traverse each segment and at each time interval. In this section, we propose a method for estimating the desired travel time using Bluetooth data.

#### 5.3.2.1 Estimation of Desired Travel Time

As illustrated in Chapter 2, there can be multiple detection (hits) for a single device in the detection zone of a detector. However, Bluetooth detections do not contain any information regarding the location of the vehicles. Therefore, multiple travel times can be estimated by matching different hits at the upstream and downstream detectors (i.e. if there are  $n$  hits at the upstream detector and  $m$  hits at the downstream detector, then there are  $n \times m$  possible estimates of travel times for this device). In travel time studies, it is a common practice that the first hit at the upstream detector be matched with the first hit at the downstream detector and this is known as first-first travel time. Other travel times can also be computed (e.g. first-last; last-first; last-last). In this research, the objective is to use these measured travel times to estimate the desired travel time that should be used for determining the optimal offset.

It is not, however, appropriate to use these measured travel times directly, because these measured travel times may include delays incurred at the upstream and/or downstream intersections (e.g. delays incurred when in the stopped queue, when decelerating to join the

queue, or accelerating when departing from the stopped queue). Figure 5-4 illustrates this phenomenon. This figure illustrates the trajectory of a sample vehicle ( $v^{th}$ ) over the road segment  $j$ . If we use the first-first travel time, we will include delays experienced at the upstream intersection (intersection  $i$ ). On the other hand if we use the last-last travel time, the delays at the downstream intersection (intersection  $i+1$ ) would be included. Rather, we wish to estimate the travel time that vehicles would experience if they did not experience these delays, but may still experience a travel time longer than the free speed travel time as a result of inclement weather, incidents, impedance due to parking manoeuvres, heavy traffic, etc. The dotted line illustrates this desired trajectory. We refer to the travel time associated with this trajectory as the *desired* travel time of vehicle  $v$  ( $tt_{desired,v}^j$ ), in order to differentiate it from the measured travel time.



**Figure 5-4: Bluetooth detection and sample trajectory of a vehicle**

The main challenge then is to estimate the platoon desired travel time given the measured travel times of vehicles. This challenge is complicated by the fact that in real-time applications the downstream intersection might be congested or poorly coordinated. In this case, the

measured travel times may all be longer than the desired travel time and many (all) of the vehicles experience delays at the downstream intersection. This delay is captured in the measured travel time and using these travel times directly to compute the offset would be incorrect and likely make the situation even worse.

Therefore, in order to solve this issue, we propose to match the last hit at the upstream detector with the first hit of the downstream detector to estimate the mid-link travel time. As illustrated in Figure 5-4, the mid-link travel time of an individual vehicle is computed as the difference between the time the vehicle is first detected at the downstream Bluetooth detector and the last time the same vehicle is detected by the upstream Bluetooth detector.

$$tt_{lf,v}^j = t_{i,v}^l - t_{i+1,v}^f \quad (5-4)$$

Where:

$t_{i,v}^l$  : Time of last hit of the  $v^{th}$  vehicle that passed intersection  $i$

$t_{i+1,v}^f$  : Time of first hit of the  $v^{th}$  vehicle that passed intersection  $i + 1$

$tt_{lf,v}^j$  : Travel time of the  $v^{th}$  vehicle in the mid-link section of segment  $j$  based on last hit at the upstream intersection and first hit at downstream intersection

The average travel speed of these vehicles is estimated as the length of road segment travelled divided by the travel time.

$$s_{mid,v}^j = \frac{L_m^j}{tt_{lf,v}^j} \quad (5-5)$$

Where:

$s_{mid,v}^j$  : Average speed of the  $v^{th}$  vehicle over the mid-link section of segment  $j$

$L_m^j$  : Length of the mid-link section of segment  $j = L^j - (l_{er}^i + l_{er}^{i+1})$

$l_{er}^i$  : Length of the effective range of detector  $i$

$L^j$  : Length of segment  $j$

Then the travel time for the entire link  $j$  can be esimated as



$$tt_{est,v}^j = \frac{L^j}{s_{mid,v}^j} \quad (5-6)$$

Where:

$tt_{est,v}^j$  : Estimated travel time of the  $v^{th}$  vehicle over the segment  $j$  with mid-link average speed ( $s_{mid,v}^j$ )

And finally, we can combine these two equations to produce

$$tt_{est,v}^j = \frac{L^j}{L_m^j} tt_{lf,v}^j \quad (5-7)$$

The main difficulty in using this expression is the uncertainty associated with  $L_m^j$ .  $l_{er}^i$  is not a fixed value (e.g. 100 meter) for each intersection and it is a function of sensor specifications, antenna characteristics, installation position of antenna, and geometry of intersection. Moreover, the first and last detections will not occur exactly at the assumed boundaries of the downstream and upstream detection zones. Therefore, we replace  $L^j/L_m^j$  with  $\alpha^j$  in Equation (5-7) and in the next section we propose a method for calibrating alpha on the basis of Bluetooth measurements.

We note that if the segment  $j$  is less than  $l_{er}^i + l_{er}^{i+1}$  (e.g. 200m) in length it is likely that the Bluetooth detection zones from the upstream and downstream detector overlap and the mid-link length will be negative. Consequently, the proposed model is only applicable for segments that are greater than  $l_{er}^i + l_{er}^{i+1}$  in length. This does not impose a significant limitation on the application of the model because in practice, it is common for signals at closely spaced intersections to be coordinated so that both signals turn green or red at the same time in order to prevent queues from spilling back to the upstream intersection. Thus for these closely spaced intersections, there is no need to dynamically adjust or optimize offsets. For the purposes of model development, it can be assumed that the mid-link section length is greater than zero.

In the event that queues, which form at the downstream intersection as a result of traffic signal operations, spill back upstream of the downstream detection zone (i.e. queue length > 100m), then the measured mid-link travel time includes delay caused by the downstream intersection. We assume that over the period of observation, at least some of the vehicles will

be able to traverse the mid-link segment ( $L_m^j$ ) without experiencing delays from the downstream intersection. Consequently, we construct the cumulative distribution of speed and travel time for all vehicles on each segment (over period  $k$ ). Then we select the  $n^{th}$  percentile travel time over the section ( $tt_j^{k,n}$ ) as representative of the desired travel time for offset optimization ( $\tilde{t}_j^k$ ) and the estimated offset for that time interval ( $O_{i,j}^k$ ) will be calculated according to Equation (5-3).

In this chapter, the value of  $n$  (travel time percentile) is determined on the basis of simulation. If the value of  $n$  is too large, then the leading cars in the platoon will arrive before the signal turns green. If the value of  $n$  is too small, then the signal will turn green before the platoon arrives at the intersection wasting capacity.

### 5.3.3 Offset Optimization Module (C)

In this chapter, we assumed that the direction of coordination in the corridor is predefined. When the system starts, the offset will be computed assuming a desired travel time equal to the posted speed limit. At the end of the first time interval, the optimal offset would be estimated using the method presented in section 5.3.2 and would be implemented. After the first time interval, the optimal offset would be recalculated using the data collected at the end of each time interval. As per Equation (5-8) if the difference between the current offset and the newly calculated offset is larger than a threshold ( $\Delta_o$ ), then the new offset will be implemented.

$$\text{if } |O_{i,j}^k - O_{i,j}^{cur}| > \Delta_o, \text{ then } O_{i,j}^{cur} = O_{i,j}^k \quad (5-8)$$

Where:

$O_{i,j}^k$  : Estimated optimal offset of the intersection  $i$  over segment  $j$  at time interval  $k$

$O_{i,j}^{cur}$  : Current offset of intersection  $i$  from segment  $j$

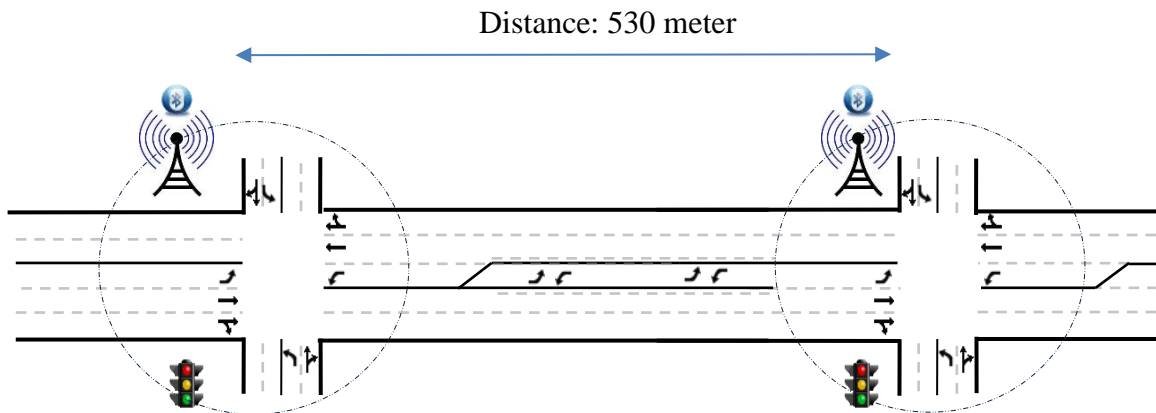
$\Delta_o$  : Threshold representing the minimum change in the offset required in order to implement a new offset.

## 5.4 Calibration and Evaluation of Proposed Methodology

We have calibrated and evaluated the proposed method using simulation as a precursor for a field evaluation. The use of simulation makes it feasible to calibrate and evaluate the proposed method over a large range of traffic conditions and simulated weather conditions; permits the direct collection of measures of performance such as desired travel time of each vehicle, measured travel time, delay, and stops; and enables direct comparisons to other offset control methods for the same traffic conditions. The BlueSynthesizer software along with Vissim was used to synthesize Bluetooth detections.

### 5.4.1 Study Network

A hypothetical segment of signalized arterial roadway with two signalized intersections was modelled as the study network. The intersections were 530 meters apart. The posted speed is 50 km/hr and  $tt_{posted}^j$  is 38.16 seconds. Figure 5-5 shows the layout of the simulated network.



**Figure 5-5 Layout of simulated network**

The signalized intersections implemented fixed-time signal timing plans with two phases; one for the main street movements and the other for the cross street movements.

Each simulation run was 180 minutes in duration. The first 15 minutes were used as the warm-up period and no data were collected during this period. Only through movements were modelled at the intersections and traffic demands were varied over time.

The trajectories of all simulated vehicles were recorded and extracted from Vissim. These were used to compute true travel times and provided as input to the BlueSynthesizer software to generate simulated Bluetooth measurements.

#### 5.4.2 Calibration of Adjustment Factor $\alpha$

The adjustment factor  $\alpha$  is used to scale up the measured last-first travel time to provide an estimate of the desired travel time over the entire segment.

When a vehicle travels at a constant speed over the length of link  $j$ , then the ratio of  $L^j/L_m^j$  will be equal to  $tt_{ll,v}^j/tt_{lf,v}^j$  and these two travel time measurements are available. We do not know the speed of a vehicle over the segment; however, if  $tt_{ll,v}^j$  is approximately equal to the free speed travel time for the segment, then we can safely assume the vehicle has not experienced delays at the downstream intersection and then the adjustment factor (for a given vehicle  $v$  on segment  $j$ ) can be computed as

$$\alpha_v^j = \frac{tt_{ll,v}^j}{tt_{lf,v}^j} \quad (5-9)$$

The adjustment factor for the segment  $j$  is computed as

$$\alpha^j = \frac{1}{V} \sum_{v=1}^V \alpha_v^j \quad (5-10)$$

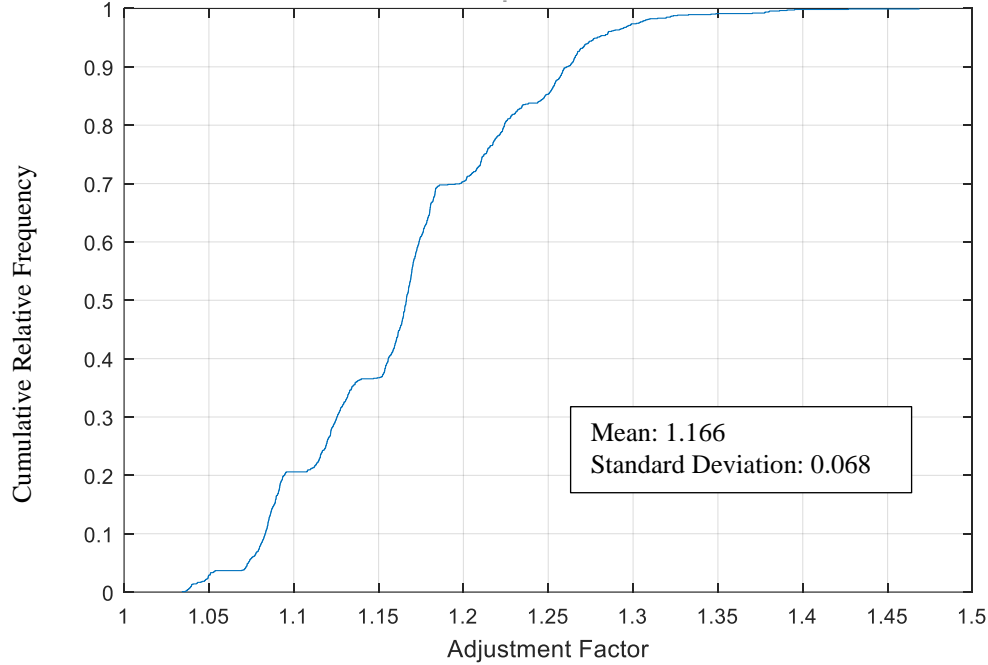
Where:

$V$  = total number of vehicles during the observation period which are deemed to travel at approximately the speed limit.

Eighteen traffic signal scenarios were designed (3 cycle lengths {60, 90, 120}, 2 g/c ratios {0.5, 0.65}, and 3 levels of progression were modelled, namely: well-coordinated, moderate coordinated, and poorly coordinated.) and each was replicated 5 times. These 90 simulation runs were used as to calibrate the adjustment factor for the study network.

There are 23850 individual Bluetooth travel times in the dataset of which 17159 have at least two hits at the downstream detector. Figure 5-6 shows the resulting distribution of the adjustment factor ( $\alpha_v^j$ ) and the adjustment factor for the segment ( $\alpha^j$ ) is equal to 1.166.

This value implies  $L_m^j = 454\text{m}$  and  $l_{er}^i$  and  $l_{er}^{i+1} = 38\text{m}$  which is consistent with expectation based on the detection zone settings used within the BlueSynthesizer software. The validity of the selected adjustment factor value is examined further in section 5.4.4.



**Figure 5-6 Cumulative Distribution Function of adjustment factor in simulated network**

It is proposed that a similar process can be used to calibrate the adjustment factor in the field. The observation period is proposed to consist of the last few days such that  $V$  is sufficiently large and alpha can adjust to changes that may occur over time. A summary of the proposed algorithm for calibration of the adjustment factor in field is below:

Step #1) Collect historical data

Step #2) Calculate free flow travel time of segment.

$$tt_{posted}^j = \frac{L^j}{S_{posted}^j} \quad (5-11)$$

Step #3) Select travel times for which there are at least two hits at downstream detector.

Step #4) Select travel times which are approximately equal to free flow travel time (difference less than 5%).

$$\frac{|tt_{ll,v}^j - tt_{posted}^j|}{tt_{posted}^j} \leq 0.05 \quad (5-12)$$

Step# 5) Calculate the adjustment factor ( $\alpha_v^j$ ) for each travel time using Equation 1-8.

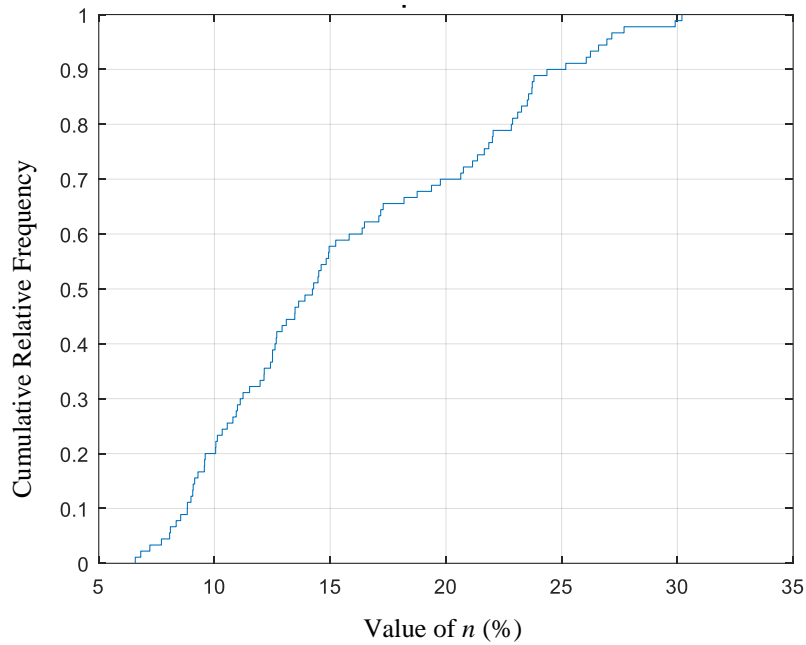
Step #6) Compute the adjustment factor for segment  $j$  using Equation 1-9.

### 5.4.3 Calibration of Travel Time Percentile ( $n$ )

In order to estimate the value of  $n$ , we need to know the true desired travel time of the platoon over the segment ( $tt_{desired}^j$ ). The true desired travel time of platoon can be observed when the platoon arrives at the downstream intersection while the signal at the downstream intersection is green and any initial queue has already been served.

In our simulated network, we obtained the true desired travel times by repeating the scenarios but with the downstream signalized intersection as being always green for the coordinated traffic (i.e. vehicle does not experience signal delay at the downstream intersection). Therefore, 6 distinct scenarios (3 cycle length with 2 g/c ratio) were replicated 5 times (30 simulation runs in total). The travel time of the each vehicle over the segment was extracted from the trajectory data and this travel time represents the true desired travel time of that vehicle. Then the true desired travel time of the segment was calculated as the average of the individual vehicle desired travel times. The estimated true desired travel ( $tt_{desired}^j$ ) in our simulation network was 38.29 seconds (almost equal to the travel time at the posted speed limit).

Then the Bluetooth travel time collected in the 90 simulation runs were adjusted using the adjustment factor estimated in section 5.4.2. For each simulation run the value of  $n$  was calculated as the inverse percentile of the estimated true desired travel time ( $tt_{desired}^j = 38.29$ ) in the set of adjusted travel times ( $\{tt_{v,adj}^{j,run}\}$ ). As a result, 90 values for  $n$  were generated. Figure 5-7 shows the cumulative distribution of the estimated percentile values ( $n$ ).



**Figure 5-7 Distribution of calibrated values of  $n$**

The data in Figure 5-7 indicate that the value of  $n$  varies substantially making the selection of a single (constant) value of  $n$  difficult to justify.

Investigation of the data indicates that there is a strong correlation between the percentile value ( $n$ ) and signal timing parameters: cycle length ( $c$ ) and green time of coordinated phase ( $g$ ). Therefore, a linear regression model was calibrated to estimate  $n$  as a function of these parameters.

$$n = 4.89 - 0.21 \times c + 0.56 \times g \quad (5-13)$$

The value of offset was not significant in the estimation of  $n$  and therefore it was excluded from the model. The model coefficients are all statistically significant (Table 5-1 ) and  $R^2 = 0.79$ .

**Table 5-1 Regression model statistical parameters**

	Coefficient	Std. Error	t	Sig.
(Constant)	4.891	1.365	3.582	.001
Cycle	-.207	.031	-6.756	.000
$g$	.563	.046	12.203	.000

The model developed in Equation (5-13) should be calibrated using field measurements for each roadway segment of interest.

In order to calibrate this model we need to have signal control parameters (cycle length, green split, and offset) from field data. Moreover, we need to have the value of true desired travel time. It is possible to estimate the desired travel time assuming vehicles travel at the posted speed limit. However, there are conditions for which the true platoon desired travel time is likely to be greater than or less than the travel time at the posted speed ( $tt_{posted}^j$ ) and therefore it is recommended to determine the true desired travel time through field observation.

The desired platoon travel time can be obtained in the field through the use of dedicated probe vehicle equipped with GPS data loggers. Another possible method would be using Bluetooth travel time measurements. Bluetooth measurements (last-last travel times) obtained over a period of several days would be collected along with weather data. Then the true desired travel time then would be estimated as a fixed percentile of the travel times obtained under clear weather conditions.

Then the same process would be performed as was carried out in this section using simulated data. For each time interval in the historical dataset, we calculate the inverse percentile of the collected Bluetooth travel time, which is equal to the true desired travel time. Then the regression model would be calibrated based on the field-collected data.

#### **5.4.4 Evaluation of Estimation of Desired Travel Time**

In order to validate the proposed method for estimation of desired travel time, we simulated two inclement weather conditions on the study network. The impact of the inclement weather is to increase the desired travel time. The desired speed profile and car following parameters of the simulated network were adjusted according to Asamer, van Zuylen et al (2013) to model the two different weather conditions. A total of 90 simulation runs for each weather condition were simulated and in each simulation run, the desired travel time was estimated using the adjustment factor and percentile model obtained from the previous section.



The true desired travel time of the arterial segment was estimated from the trajectory of vehicles when the downstream intersection was set to be green all the time. Table 5-2 shows the summary of the results.

**Table 5-2: Validation of proposed model for estimating desired travel time**

		True Desired Travel Time (seconds)	Absolute Relative Error (%)		Absolute Error (seconds)	
			Average	Max	Average	Max
Weather	Weather 1	50.39	3.5%	10.5%	1.7	5.3
	Weather 2	71.8	7.6%	15.9%	5.5	11.4

From the results, we can observe that the proposed estimation model can estimate the true desired travel time from Bluetooth data with an average absolute relative error of less than 8% and that maximum absolute relative errors are less than 16%. These results are encouraging; however, the more important evaluation is the impact that the estimates travel time has on the optimization of the offset. This evaluation is described in the next section.

#### 5.4.5 Evaluation of Proposed Method for Offset Optimization

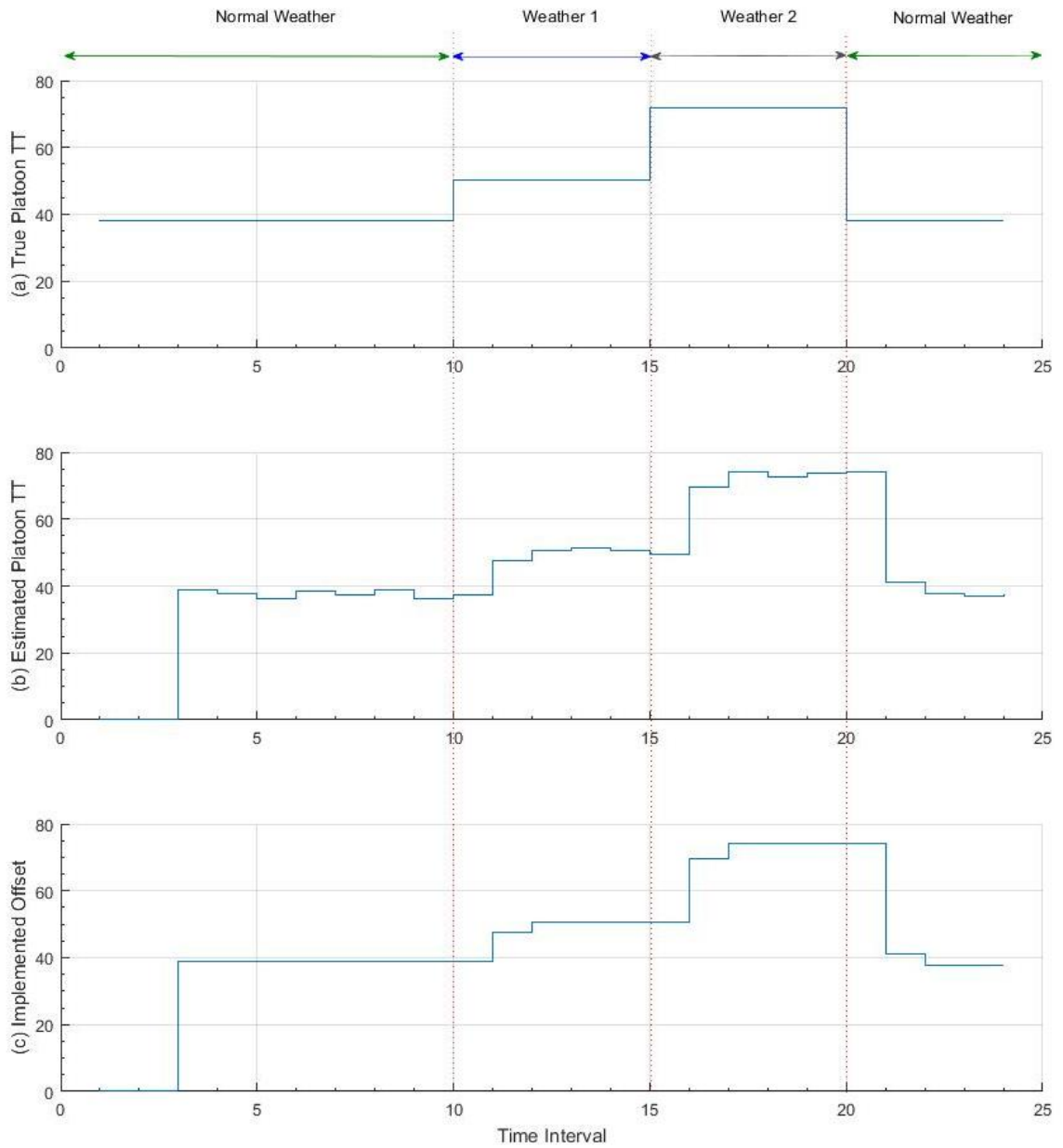
In order to implement the proposed green split optimization algorithm, the optimization framework, *BlueOptimizer*, was developed further to implement offset optimization. At each update interval, it measures the Bluetooth travel time and applies the adjustment factor ( $\alpha^j$ ). Then it optimizes the offset according to the proposed method and updates the traffic signal timing plans for implementation in Vissim for the next time interval.

The study network described previously was used to evaluate the proposed methodology. The duration of simulation is 21,600 seconds (24 fifteen-minute time intervals). The first 1800 seconds is allocated for warm up. The signal controller starts to collect Bluetooth travel time information after 1800 seconds. After 15 minutes of data collection, the optimization starts at time 2700 seconds (time interval 3). In this simulation, we set  $\Delta_o$  to 3 seconds. We assumed the level of market penetration (LMP) for Bluetooth devices is 10%. We set the minimum required number of travel time measurements in the data aggregation interval ( $N_{min}$ ) equal to

10. The optimization time interval ( $\Delta t_o$ ) was set to 15 minutes. The minimum data aggregation interval duration ( $\Delta t_a^{min}$ ) was set equal to 15 minutes and the maximum data aggregation interval duration ( $\Delta t_a^{max}$ ) was set equal to 30 minutes. Furthermore, we used a simplified rule for incrementally increasing the duration of  $\Delta t_a^k$ . If there were insufficient number of observations in 15 minutes, we increased the duration of  $\Delta t_a^k$  to 30 minutes.

The traffic demand on each approach was set to 1000 vehicle per hour. Three different weather conditions were modelled in the network over time as illustrated in Figure 5-8. As a result, the true desired travel time varies over time as illustrated in Figure 5-8 (a).

Figure 5-8 (b) shows the estimated desired travel time at the beginning of each time interval. The simulation starts with initial offset value of zero (poor coordination). At time interval 3, the offset optimization process begins and sets the offset to 38.99 seconds based on estimated desired travel time (Figure 5-8 (c)). The simulation continues until at time interval 10 in which the weather 1 condition occurs and desired travel time starts to increase. The system detects the changes in desired travel time and optimizes the offset accordingly (50.65 seconds). Starting at time interval 15, the weather condition gets worse (weather condition 2); desired travel times increase, and the system responds by increasing the offset to 73.92 seconds. At time interval 20, normal weather conditions return and offset is reduced to 37.77 seconds.



**Figure 5-8: Illustrative sample of simulation data**

## 5.5 Results

In order to evaluate the performance of the proposed methodology, the network was simulated with two different types of traffic signal control strategies, namely: (1) fixed offset

plans for which the optimum offset was determined using the Synchro software for normal weather condition; (2) the proposed dynamic offset optimization.

The performance of the proposed offset optimization method was evaluated across normal weather and the two inclement weather conditions which were used in the previous section.

Each of the 3 weather conditions was simulated 5 times, each time with a different random seed for each of the two offset control strategies (30 simulations in total). The average delay of the coordinated movement at the downstream intersection was computed for each simulation and averaged across the five replications as the measure of performance.

Table 5-3 shows the resulting average vehicle delay of coordinated movement for the three weather conditions for the two offset control methods. For each combination, we computed the difference in the mean of average vehicle delay between the proposed offset optimization strategy and the fixed strategy. Using the t-test we determined if the difference in means was statistically significant at the 95% confidence level. If the difference was statistically significant, we report the associated relative change in delay (positive is a reduction in delay). If the mean delays were not statistically different, then we have reported "Equal" in the cell.

**Table 5-3: Performance of the proposed method (average vehicle delay)**

		Average Delay (seconds)		Improvement
		Fixed Offset	BT Offset Optimization	
Weather	Normal	3.56	3.70	Equal
	Weather 1	18.56	9.38	49%
	Weather 2	50.85	12.24	76%

From the results, we can observe that the proposed offset optimization performs equal to the fixed time strategy under normal weather conditions. This result is expected and shows the proposed optimization method can estimate offset from Bluetooth data correctly. We also observe that when inclement weather conditions occur and impact vehicle speeds, the proposed

optimization strategy performs better than the fixed strategy and provides reductions in average delay that range from 49% to 76% depending on the weather condition.

## **5.6 Conclusions and Recommendations**

In this chapter, we proposed a method to optimize offset in a corridor using travel time data obtained from Bluetooth detectors. The proposed method has been evaluated for a range of traffic demands and weather conditions using a custom-built simulation framework. Furthermore, an analysis was performed to estimate the optimal set of control parameters.

The proposed method provides substantial benefits when the network experiences changes in desired travel time such as inclement weather. Simulation results indicate that the proposed method can provide up to 75% reduction in average vehicle delay for vehicles discharging in the coordinated phase in comparison with fixed offset timing in different weather conditions.

The overall results suggest that the proposed method is able to optimize the offset, reduce coordinated phase delay and improve level of service using only data obtained from Bluetooth detectors in real-time.

# Chapter 6

## Conclusions and Recommendations

### 6.1 Conclusions

In recent years, Bluetooth technology has been adapted for use as a sensor for measuring vehicle travel times along a segment of roadway. However, using Bluetooth technology in ATMS such as advanced traffic signal controls has been limited in part because there has been little research conducted to investigate the opportunity to estimate intersection control delay using Bluetooth collected data. Furthermore, until recently, there has been a lack of tools, such as simulation, to predict the behavior of the system before it is developed and deployed. Therefore, the main intention of this research was to develop a robust framework for adaptive signal control using Bluetooth detectors as the main source of data.

In this thesis, we addressed the aforementioned challenges and proposed an integrated framework for real time adaptive traffic signal management using Bluetooth data. The main contributions of this research and the direction for further studies are described in this chapter.

### 6.2 Major Contributions

The following describes the major contributions of this research to the state of the art and practice:

1. *Development of a Simulation of Bluetooth Inquiry Process for Application in Transportation Engineering:* I have developed a state of art simulation framework to simulate the Bluetooth detection process. The proposed Bluetooth simulation model was validated using field measurements collected using a custom-built system of hardware and software. The field data showed that the proposed simulation model provides a high level of accuracy of the Bluetooth detection process, both in terms of the time between successive detections and the distribution of the location of the detection. These results suggest that the proposed simulation model is suitable for evaluating traffic management strategies, which rely on Bluetooth detections.

The developed simulation framework was combined with commercially available traffic microsimulation models to evaluate and develop the use of Bluetooth technology within ATMS.

2. *Estimation of Control Delay at Signalized Intersections using Bluetooth Detectors:* Two methods have been developed to estimate control delay using data available from Bluetooth detectors. Method 1 requires data from a single Bluetooth detector deployed at the intersection and estimates delay on the basis of the measured Bluetooth dwell time. This model has a high level of accuracy when queue length is less than the effective range of the Bluetooth detectors but performs poorly when queues exceed the detector range. Method 2 uses Bluetooth measured travel time to estimate control delay. This method requires data from two Bluetooth detectors, one at the intersection and one upstream. This method can be used regardless of the length of queues and provides a high level of accuracy in any condition.

The overall results suggest that the proposed methods are suitable for estimation of intersection delay using Bluetooth detectors. The estimated delay can be used as the key measure of performance for an intersection in offline and in online applications. This could be the basis of advanced traffic management systems and advanced traveler information systems that rely on Bluetooth measurements.

3. *Adaptive Green Split Optimization of Signalized Intersections Using Bluetooth Technology:* I proposed a method to optimize green splits at an isolated intersection using control delay estimates from Bluetooth detector data. The proposed method has been evaluated for a range of traffic demands using the custom-built simulation framework. Furthermore, a sensitivity analysis was performed to estimate the optimal set of control parameters. The proposed method can provide up to 50% reduction in average delay in comparison with fixed signal timing and fully actuated controller. When the traffic volumes are very low, the proposed method does not provide improved performance because there are insufficient number of vehicles detected to provide reliable estimates of control delay. The level improvement can vary in field because of outliers, possible spillbacks from the downstream intersection, and rapid variation of traffic demand. The overall results suggest that the proposed method is able to

optimize the green splits, reduce intersection delay and improve level of service using only data obtained from Bluetooth detectors.

4. *Adaptive Offset Optimization of Signalized Intersections Using Bluetooth Technology:*  
In this research, I proposed a method to estimate the desired travel time of platoons in real time using travel time data obtained from Bluetooth detectors. I have also proposed a framework to dynamically optimize traffic signal offsets along a corridor using the estimated desired travel time. The proposed method has been evaluated for a range of traffic demands and weather conditions using the custom-built simulation framework. Furthermore, calibration was performed to estimate the optimal set of control parameters. The proposed method provides substantial benefits when the network experiences changes in desired travel time such as under inclement weather conditions. The overall results suggest that the proposed method is able to optimize the offset, reduce coordinated phase delay and improve level of service using only data obtained from Bluetooth detectors in real-time.

### **6.3 Future Research**

The following topics improve and complement this research and therefore are recommended for future research:

1. In this research, we assumed that the cycle length, the number of/structure of the signal timing phases, and the direction of coordination are predefined and known. However, it would be beneficial to be able to dynamically optimize the cycle length and direction of coordination using the Bluetooth collected data.
2. The proposed method is based on the assumption that mid-block intersections/driveways may exist on the approach links between the Bluetooth detectors, but the traffic on the approach link is not subject to traffic signal or stop controls at these intersections (i.e. only the cross street or driveway would be controlled). It is recommended to investigate the cases where the approach link is subject to traffic signal or stop controls. If the system is able to function in these cases, we will not need to install Bluetooth detectors and/or signal controller on every



intersection in the corridor. This would lower installation and maintenance cost of the system permitting deployment on a larger number of corridors.

3. The current optimization modules are based on rule-based algorithms. There is a potential to improve the algorithm by using a more robust control method (e.g. artificial intelligence, reinforced learning, etc.).
4. Proactive traffic management (PTM) is “generally regarded as an approach for dynamically managing and controlling traffic demand and available capacity of transportation facilities, based on prevailing traffic conditions, using one or a combination of real-time and predictive operational strategies” (Brinckerhoff, Farradyne & Burgess 2008). Fusion of the proposed algorithm with near future prediction of travel time and delay would result in a proactive traffic signal control system that could further improve road network operation.
5. Bluetooth obtained data are considered as the only input for the developed algorithms. However, incorporating data from other traffic sensor technologies (e.g. camera system) with Bluetooth detectors has the potential to provide even greater performance improvements.
6. The proposed algorithms are developed based on a field-tested simulation framework. Our field tests showed us that the developed simulation framework provides a reasonable level of accuracy. However, we believe the next step would be to evaluate the performance of the proposed models and algorithms in a real-world roadway section empirically (an intersection or ideally an arterial corridor) and calibrate the algorithms and parameters using field measurements.

## References

- Abbas, M., Rajasekhar, L., Gharat, A. & Dunning, J.P. 2013, "Microscopic modeling of control delay at signalized intersections based on Bluetooth data", *Journal of Intelligent Transportation Systems*, vol. 17, no. 2, pp. 110-122.
- Araghi, B.N., Pedersen, K.S., Christensen, L.T., Krishnan, R. & Lahrmann, H. 2015, "Accuracy of travel time estimation using Bluetooth technology: Case study Limfjord tunnel Aalborg", *International Journal of Intelligent Transportation Systems Research*, vol. 13, no. 3, pp. 166-191.
- Asamer, J., van Zuylen, H.J. & Heilmann, B. 2013, "Calibrating car-following parameters for snowy road conditions in the microscopic traffic simulator VISSIM", *IET Intelligent Transport Systems*, vol. 7, no. 1, pp. 114-121.
- Bachmann, C., Roorda, M.J., Abdulhai, B. & Moshiri, B. 2013, "Fusing a bluetooth traffic monitoring system with loop detector data for improved freeway traffic speed estimation", *Journal of Intelligent Transportation Systems*, vol. 17, no. 2, pp. 152-164.
- Bakula, C., Schneider IV, W.H. & Roth, J. 2011, "Probabilistic model based on the effective range and vehicle speed to determine Bluetooth MAC address matches from roadside traffic monitoring", *Journal of Transportation Engineering*, vol. 138, no. 1, pp. 43-49.
- 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*, vol. 2175, no. 1, pp. 19-27.
- Bluetooth Special Interest Group 2014, , *Bluetooth Core Specification 4.2*. Available: <https://www.bluetooth.org/en-us/specification/adopted-specifications> [2015, .
- Brinckerhoff, P., Farradyne, T. & Burgess, J.C. 2008, "Active Traffic Management Concept of Operations", *Seattle, WA: Washington State Department of Transportation*, .
- Cabero, J.M., Molina, V., Urteaga, I., Liberal, F. & Martín, J.L. 2014, "Acquisition of human traces with Bluetooth technology: Challenges and proposals", *Ad Hoc Networks*, vol. 12, pp. 2-16.
- Cho, K., Park, G., Cho, W., Seo, J. & Han, K. 2015, "Performance analysis of device discovery of Bluetooth Low Energy (BLE) networks", *Computer Communications*, .
- Cho, K., Park, W., Hong, M., Park, G., Cho, W., Seo, J. & Han, K. 2014, "Analysis of latency performance of Bluetooth low energy (BLE) networks", *Sensors*, vol. 15, no. 1, pp. 59-78.

- Curtis, E. 2010, *Adaptive Signal Control Technology Overview*, FHWA Office of Operations.
- Das, A., Ghose, A., Razdan, A., Saran, H. & Shorey, R. 2001, "Enhancing performance of asynchronous data traffic over the Bluetooth wireless ad-hoc network", *INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, , pp. 591.
- Day, C.M. & Bullock, D.M. 2016, "Detector-Free Signal Offset Optimization with Limited Connected Vehicle Market Penetration: Proof-of-Concept Study", *Transportation Research Record: Journal of the Transportation Research Board*, , no. 2558, pp. 54-65.
- Day, C.M., Haseman, R., Premachandra, H., Brennan, T., Wasson, J.S., Sturdevant, J.R. & Bullock, D.M. 2010, "Visualization and assessment of arterial progression quality using high resolution signal event data and measured travel time", *Transportation Research Record*, , no. 2192, pp. 37-49.
- Díaz, J.J.V., González, A.B.R. & Wilby, M.R. 2016, "Bluetooth Traffic Monitoring Systems for Travel Time Estimation on Freeways", *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 1, pp. 123-132.
- FHWA 2008, *FHWA Traffic Signal Timing Manual*, U.S. Department of Transportation Federal Highway Administration, Washington, D.C.
- Fresnedo, O., Iglesia, D.I. & Escudero, C.J. 2007, "Bluetooth inquiry procedure: optimization and influence of the number of devices", *Proceedings of the Sixth IASTED International Conference on Communication Systems and Networks* ACTA Press, , pp. 205.
- Goodall, N., Smith, B. & Park, B. 2013, "Traffic signal control with connected vehicles", *Transportation Research Record: Journal of the Transportation Research Board*, , no. 2381, pp. 65-72.
- Haghani, A., Hamedi, M., Sadabadi, K.F., 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*, vol. 2160, no. 1, pp. 60-68.
- Hu, Y. & Hellinga, B. 2013, *Short-term Prediction of Freeway Travel Times Using Data from Bluetooth Detectors*, University of Waterloo.
- Hunt, P., Robertson, D., Bretherton, R. & Winton, R. 1981, *SCOOT-a traffic responsive method of coordinating signals*, .
- IBM Research 2001, *Bluehoc Simulator*.
- IEEE Standards Association 2005, *IEEE Standard for Information technology Telecommunications and information exchange between system Local and metropolitan area networks Specific requirements. Part 15.1: Wireless medium access control (MAC)*

*and physical layer (PHY) specifications for wireless personal area networks (WPANs), IEEE.*

Isaksson, L. & Fiedler, M. 2004, "Optimization of the random backoff boundary of the bluetooth fhss technique", *COST 279, Technical Document 279 TD (04) 027, 11 th Management Committee Meeting, Ghent, Belgium.*

iTRANS 2006, *Costs of Non-Recurrent. Congestion in Canada. Final Report, Ottawa.*

Jiang, J., Lin, B. & Tseng, Y. 2004, "Analysis of Bluetooth device discovery and some speedup mechanisms", *Journal of the Institute of Electrical Engineering*, vol. 11, no. 4, pp. 301-310.

Lowrie, P. 1982, "The Sydney coordinated adaptive traffic system-principles, methodology, algorithms", *International Conference on Road Traffic Signalling, 1982, London, United Kingdom.*

Luyanda, F., Gettman, D., Head, L., Shelby, S., Bullock, D. & Mirchandani, P. 2003, "ACS-Lite algorithmic architecture: applying adaptive control system technology to closed-loop traffic signal control systems", *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1856, no. 1, pp. 175-184.

Malinovskiy, Y., Lee, U., Wu, Y. & Wang, Y. 2011, "Investigation of bluetooth-based travel time estimation error on a short corridor", *Transportation research board 90th annual meeting.*

Mirchandani, P. & Head, L. 2001, "A real-time traffic signal control system: architecture, algorithms, and analysis", *Transportation Research Part C: Emerging Technologies*, vol. 9, no. 6, pp. 415-432.

MIT NMS Group 2002, *Blueware: Bluetooth simulation for NS.*

Moghaddam, S.S. & Hellinga, B. 2014, "Real-Time Prediction of Arterial Roadway Travel Times Using Data Collected by Bluetooth Detectors", *Transportation Research Board 93rd Annual Meeting.*

Moghaddam, S.S. & Hellinga, B. 2013, "Quantifying Measurement Error in Arterial Travel Times Measured by Bluetooth Detectors", .

Mohrehkesh, S. & Nadeem, T. 2014, "Optimized inquiry mechanisms for Bluetooth devices.", *ICC*, pp. 421.

Park, H. & Haghani, A. 2014, "Use of bluetooth technology on mobile phones for optimal traffic signal timing", *MOBILITY: The Fourth International Conference on Mobile Services, Resources, and Users.*

- Parvatham, S. 2002, *Bluesim: A Bluetooth LAN Access Profile Simulator*, .
- Peterson, B.S., Baldwin, R.O. & Kharoufeh, J.P. 2006, "Bluetooth inquiry time characterization and selection", *Mobile Computing, IEEE Transactions on*, vol. 5, no. 9, pp. 1173-1187.
- Pooran, F. & Farradyne, P. 2000, "Optimized Policies for Adaptive Control (OPAC)", *Workshop on Adaptive Traffic Signal Control Systems, 79th Annual Meeting of the Transportation Research Board, Washington, DC*.
- Porter, J.D., Kim, D.S., Magaña, M.E., Poocharoen, P. & Arriaga, C.A.G. 2013, "Antenna characterization for Bluetooth-based travel time data collection", *Journal of Intelligent Transportation Systems*, vol. 17, no. 2, pp. 142-151.
- Quayle, S.M., Koonce, P., DePencier, D. & Bullock, D.M. 2010, "Arterial Performance Measures with Media Access Control Readers", *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2192, no. 1, pp. 185-193.
- Stevanovic, A. 2010, *Adaptive traffic control systems: Domestic and foreign state of practice*, .
- Teply, S., Allingham, D., Richardson, D. & Stephenson, B. 2008, "Canadian capacity guide for signalized intersections", .
- Thamrin, T. & Sahib, S. 2009, "The inquiry and page procedure in Bluetooth connection", *Soft Computing and Pattern Recognition, 2009. SOCPAR'09. International Conference of IEEE*, , pp. 218.
- Transportation Research Board 2010, *Highway capacity manual*, Washington, DC.
- Webster, F. 1958, "Traffic signal settings, road research technical paper no. 39", *Road Research Laboratory*, .
- Záruba, G.V. & Chlamtac, I. 2003, "Accelerating Bluetooth inquiry for personal area networks", *Global Telecommunications Conference, 2003. GLOBECOM'03. IEEEIEEE*, , pp. 702.
- Zhang, W., Zhu, H. & Cao, G. 2002, "Improving Bluetooth network performance through a time-slot leasing approach", *Wireless Communications and Networking Conference, 2002. WCNC2002IEEE*, , pp. 592.