# Use of Bluetooth Technology on Mobile Phones for Optimal Traffic Signal Timing

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***Abstract*— Optimizing traffic signal timing is an effective and economical way to improve mobility in an urban area and reduce traffic congestion. The objective of the proposed algorithm is to enable traffic to traverse through the maximum number of downstream intersections without a stop. In this study, Bluetooth technology, to measure travel times on arterial roads, is used as input for an optimal bandwidth progression algorithm. The trajectories of vehicle platoons are tracked and decomposed into link-based samples using adaptive smoothing method, and paired with signal timing on each signalized intersection. Predicted travel time, a value representing the travel time between signalized intersections, is obtained by Support Vector Regression (SVR) model. According to bandwidth efficiency and attainability, the signal timing generated by the proposed model yields lower delays than the current signal planning. The applicability of the proposed model has been validated.**

***Keywords-Bluetooth technology; bandwidth optimization; adaptive smoothing; support vector machine***

## I. INTRODUCTION

Mobility is a key performance area, the enhancement of which supports the economy and the community by facilitating the movement of people and goods [1]. It is critical to maintain reliable traffic flow: travelers can plan and execute their journeys seamlessly using available software applications, and vehicles will flow more freely through existing infrastructure. To overcome the increasing congestion of arterial roads, investments on infrastructure have increased. However, expanding infrastructure is not the only way to improve mobility. Making better use of existing roads can also increase transport capacity.

Arterial street signal systems must coordinate timing of adjacent intersections to improve mobility of platoons. Vehicles in the platoons could encounter fewer red lights, shortening the travel time, decreasing number of stops, and reducing time delays. Bandwidth efficiency and attainability are major criteria for judging the quality of a coordinated signal timing plan. Bandwidth-based solutions, the most visible indicator to individual drivers, generally outperform delay-based solutions [2]. To provide an optimal bandwidth progression, traffic engineers are faced with problems of providing accurate travel time between intersections. Various models have been developed to accurately estimate arterial travel times or delays. However, collecting reliable traveling time data on signalized intersections is challenging. Previous sensor technologies have issues with privacy protection, quality of data, and cost of dedicated hardware.

The number of mobile phones used worldwide has grown, and more than half of those were smartphones in 2013 [3]. Wireless communications are considered enablers of innovation in the field of smart mobility in smart cities [4]. Therefore, it will be worthwhile to identify vehicles carrying mobile phones. One of the latest technologies using wireless communication is the Bluetooth detector, becoming more common to enable real-time continuous traffic monitoring. This paper introduces Bluetooth technology as an effective means of data collection of ground truth travel time. Measured travel time data is used as input for an optimal bandwidth progression algorithm. Compared to traditional method depending on point speed at their fixed locations, Bluetooth technology provide point-to-point travel time over the segments. A new traffic light based on traffic data collected by Bluetooth technology also make traffic flow more smooth and fast [5]. By placing sensors along roads, tracking Bluetooth devices in passing vehicles, the solution is able to accurately detect and record how long it takes a car to drive along a corridor, segment by segment. Fig. 1 presents a well-configured signal coordination system using Bluetooth technology.

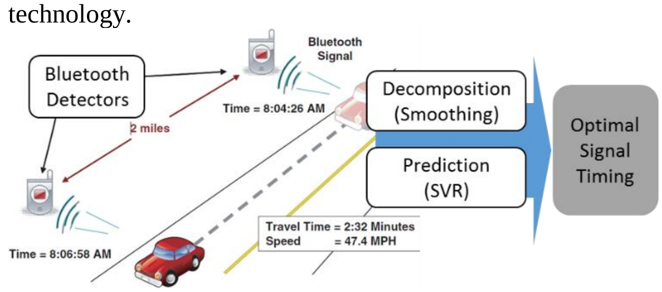


Figure 1. A signal coordination system for arterial roads

The trajectories of vehicle platoons are tracked and decomposed into link-based samples in this study. However, Bluetooth sensors, collecting the data in a point-to-point format, may not be used directly for real-time purposes. It takes time for the actual trip to be realized and for the travel time to become available. In most urban networks, the actual travel time is not available within one discrete time step, as traffic congestion increases. Therefore, we use predicted values of link travel time. The performance of travel time prediction varies with many variables, such as day-to-day traffic demand and other factors. Considering the complex and dynamic nature of traffic flows in the system, traditional models cannot capture the complete characteristics of the stochastic traffic data and may not predict the traffic under

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variation with high accuracy. We develop Support Vector Regression (SVR) to predict link travel time.

The Bluetooth technology is introduced for travel time data collection in Section II. Usages of travel time for optimal signal timing is proposed in Section III. We present decomposition and prediction of travel time in Section IV. The signal timing plan is evaluated and future work is presented in Section V and Section VI, respectively.

## II. STATE-OF-THE-ART

### A. Sensor Technologies

Accurate travel time information between two intersections can be essential to get optimal signal coordination, yet reliable methods for travel surveillances are slow in coming.

*1)* Until recently, inductive *loop* detectors [6] were the most common traffic data collection for arterial streets even though they are not always reliable. These sensors disrupt traffic during installation and repair, and therefore have high installation and maintenance costs.

*2)* *License plate matching* has been used to travel time data collection purpose. However, this system have high equipment costs and their accuracy depends on environmental conditions.

*3)* *Acoustic* sensors are attractive especially for their low cost and simple and non-intrusive installation. However they require a sophisticated post-processing algorithm for extracting useful information [7]. These sensors depend on measurements at a point that will over-represent the number of fast vehicles and under-represent the slow ones, and hence give a higher average speed than the true average.

*4)* Recently, mobile phones have been used as primary source of floating car data. A camera-based traffic signal detection algorithm was used to learn traffic signal schedule patterns and predict their future schedule. Based on when the signal ahead will turn green, drivers can then *adjust speed* so as to avoid coming to a complete halt [8]. It is also possible to accurately infer traffic volume through *Global Positioning Systems* (GPS) collected from a roving sensor network of taxi probes that log their locations and speeds at regular intervals [9]. However, energy consumption of GPS on some phones can be a challenge, then less energy-hungry but noisier sensors like WiFi can be used to estimate both a user's trajectory and travel time along the route [10].

### B. Bluetooth Technology

The traditional floating car method is very costly and produces a sparse amount of data [11]. As a result, a new data collection methodology was developed that receives anonymous emissions from Bluetooth equipped accessories in passing vehicles that have been activated in the discovery mode. Bluetooth technology is good for collecting high-quality travel time data that can be used as ground truth for evaluating other sources of travel time [12]. This method proved to be more cost-efficient than floating car method. Various application of Bluetooth technology can be found in [13].

Bluetooth is a telecommunications industry specification that defines the manner in which mobile phones, computers, personal digital assistants, car radios, and other digital devices can be easily interconnected using short-range wireless communications. One example of the use of this technology is the interconnection of a mobile phone with a wireless earpiece to permit hands-free operation. Bluetooth enabled devices can communicate with other Bluetooth-enabled devices anywhere from 1 m to about 100 m (300 ft). This variability in the communications capability depends on the power rating of the Bluetooth sub-systems in the devices. The Bluetooth protocol uses a 48-bit electronic identifier, or tag, in each device called a Machine Access Control (MAC) address. Bluetooth transceivers transmit their MAC ID for the purpose of identifying a device with which to communicate. This "inquiry mode" is used to establish a link with the "responding devices." Inquiries are made by a Bluetooth transceiver, even while it is already engaged in communication with another device. The continuous nature of this process facilitates the identification of passing vehicles containing Bluetooth devices, since all equipped and activated devices will be transmitting inquiries as long as they have their discovery mode enabled.

The main purpose of this paper is a *temporary* (i.e., two weeks) installation of sensors on a small network. Our future study also includes dynamic installations of sensors so that sensors can cover the entire network in several stages [14]. However, there is a case for *permanent* installation of Bluetooth sensors running on solar energy with an overall power budget of less than 5 watts. For details on the technology, readers can refer to [15].

The Bluetooth traffic monitoring system calculates travel times by matching public Bluetooth wireless network IDs at successive detection stations. The time difference of the ID matches provides a measure of travel time and space mean speed based on the distance between the successive stations. Each vehicle at the same signal timing in a different time of day is categorized to represent vehicle platoon.

### C. Data Quality Issues

Although Bluetooth has been demonstrated as a promising technology, there remain problems which affect the accuracy of the estimation such as difficulty of distinguishing between multiple transportation modes (e.g., passenger cars, buses, bicycles, or pedestrians.). For example, the probability of multiple Bluetooth travel time records from a bus was analyzed [16]. It is observed that bus is overrepresented in the BMS dataset and it is rare to have overrepresentation by more than six travel time points. The chances of observing more than three travel time records for a bus, is less than 20 %. Nevertheless, in our study, there is no data suspected to be other mode than motor vehicles. However, an effort to distinguish different transportation mode may need in more congested urban area.

The Bluetooth receiver can pick up signals within a 300-ft radius around the sensor. Having two sensors at both ends of an arterial segment implies that in the resulting travel time samples obtained using this technology, one might expect to see errors caused by a maximum of 600-ft error in the length traveled. Since Bluetooth devices might be detected at any point within the detection zone, this study used the first detection in a group to calculate travel times from the MAC address data.

The Bluetooth traffic detectors sample only a fraction of the vehicles in the traffic stream. To approximate the sampling ratio of the new technology, actual traffic volume in a roadway segment is needed. Traffic volume data are available where other sources of traffic surveillance systems are in place. The average Bluetooth hourly sampling rate is between 2.0% and 3.4%.

### D. Privacy Concerns

The anonymous nature of this technique is due to the use of MAC addresses as identifiers. MAC addresses are not directly associated with any specific user account (as is the case with cell phone geo-location techniques) or any specific vehicle (as is the case with deriving travel time from automated toll tags). The MAC address of a cell phone, camera, or other electronic devices, though unique, is not linked to a specific person through any type of central database thus minimizing privacy concerns. Additionally, users concerned with privacy can set options in their device (referred to as "Discovery Mode" or "Visibility") so that the device is not detectable.

## III. BANDWIDTH OPTIMIZATION ALGORITHMS

Bandwidth optimization algorithm using three signals with simple two-phase operations is illustrated (Fig. 2). An intersection with the minimum arterial green split, $G_{\min}$, is called the critical intersection (e.g., the middle intersection). The arterial green times for the other intersections in the system are all greater than $G_{\min}$. This minimum green time, $G_{\min}$, determines the largest possible bandwidth progression that can be achieved for the system.

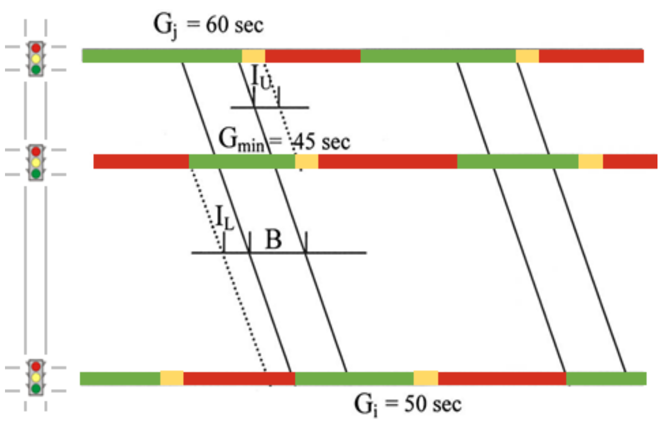


Figure 2. Optimization of bandwidth progression

The system bandwidth is reduced if the progression band encounters interference from other signals in the system. Only one type of interference, either an upper interference, $I_U$, or a lower interference, $I_L$, can occur at each signal. The final system bandwidth, $B$, is determined by $G_{\min}$ minus the minimum possible combination of the upper interference and the lower interference,

$$B = G_{\min} - \min\{\max(I_{U,i}) + \max(I_{L,j})\} \quad (1)$$

where B=bandwidth(s); $I_{U,i}$=upper interference at intersection i (s); $I_{l,j}$ lower interference at intersection j (s); $\max(I_{U,i})$=maximum value from all signals producing upper interference and max maximum value from all signals producing lower interferences.

The enhanced Brook's algorithms [17], such as those in PASSER II [18], search for the best phasing sequences and offsets at each signal location to minimize the combined interference. The optimization process simultaneously considers progression in both directions.

To maximize the progression bandwidths for both directions, the offset and phasing of each signal should be carefully designed. For an intersection $j$ with multi-phases (e.g., the option of a leading left turn phase or a lagging left turn phase), the interference for one direction is also related to the timing parameters for the other direction. Equations (2) and (3) show how the upper interference or the lower interference can be calculated for intersection $j$ with respect to a master intersection $m$ for one of the directions

$$I_{U,j}(p) = [G_{\min} - T_{mj} + T_{jm} - O_m(n) + O_j(p) + G_j] \bmod C \quad (2)$$

$$I_{L,j}(p) = [T_{mj} + T_{jm} - O_m(n) + O_j(p) - S_j] \bmod C \quad (3)$$

where $I_{U,i}(p)$, $I_{L,j}(p)$=upper interference and lower interference at intersection $j$ with phase sequence $p$ (only one phase sequence could occur) (s); $T_{mj}$, $T_{jm}$=travel times between intersections $m$ and $j$ (s); $O_m(n)$=relative offset between direction $a$ green time and direction $b$ green time at signal $m$ with phase sequence $n$ (s); $O_j(p)$=relative offset between direction $a$ green time and direction $b$ green time at signal $j$ with phase sequence $p$ (s); $G_j$=direction $a$ green time at signal $j$ (s); $S_j$=difference between green times of intersections $j$ and $m$ in direction $b$ (s); and $C$=cycle length (s).

The interference (either upper or lower) is largely affected by the signal spacing as reflected by the travel times, $T_{mj}$ and $T_{jm}$. Representative travel time has been predicted by using decomposition and SVR in travel time prediction section of this paper. With the increase of the number of signals in a system, the chances of having larger interference values also increase. For example, there might be a signal whose spacing may actually produce maximum interference, which equals to $G_{\min}$, the green time of the reference intersection. In this case, the bandwidth would be zero.

The arrival sequence of green time at each intersection presents four scenarios.

- Scenario 1. upstream bands projected to arrive after downstream queue discharges
- Scenario 2. upstream bands projected to not arrive after downstream queue discharges
- Scenario 3. upstream bands projected to arrive before queue discharges

- Scenario 4. upstream bands projected to arrive after downstream queue discharges

To evaluate the proposed algorithm, delay is calculated for each vehicle compare to free flow traffic condition. Calculated delay for each signal cycle at specific time of day is aggregated for forty seven days. Efficiency and attainability measure the quality of through progression provided by a timing plan. Efficiency for a direction is the percent of cycle used for progression. Attainability is the percent of bandwidth in a direction in relation to the minimum green split in the same direction. When attainability is at 100%, the bandwidth is at its maximum. Theoretically, the maximum bandwidth in a direction can be no more than the smallest through green split in that direction. We calculate efficiency and attainability for the two arterial directions (4) and (5).

$$\text{Efficiency}(\%) = \frac{(\mathrm{B_U} + \mathrm{B_L})}{2 \times \text{Cycle length}} \times 100 \tag{4}$$

$$\text{Attainability}(\%) = \frac{(\mathrm{B_U} + \mathrm{B_L})}{G_{\min, \mathrm{U}} + G_{\min, \mathrm{L}}} \times 100 \tag{5}$$

## IV. Arterial Travel Time

While license plate matching techniques are several miles apart due to associated costs, Bluetooth sensors are deployed 0.7-1 miles apart. A normal segment between Bluetooth sensors has two or three intermediate intersections. Proposed decomposition method reconstructs the trajectory of point-to-point path into intersection to intersection link data. Accurate prediction of travel time provides inputs for optimal bandwidth progression.

### A. Decomposition of Path Travel Time

For a vehicle traveling from an origin point *A* to a destination point *B* through *x* intersections, we decompose the travel time as the sum of travel times on each link (Fig. 3).

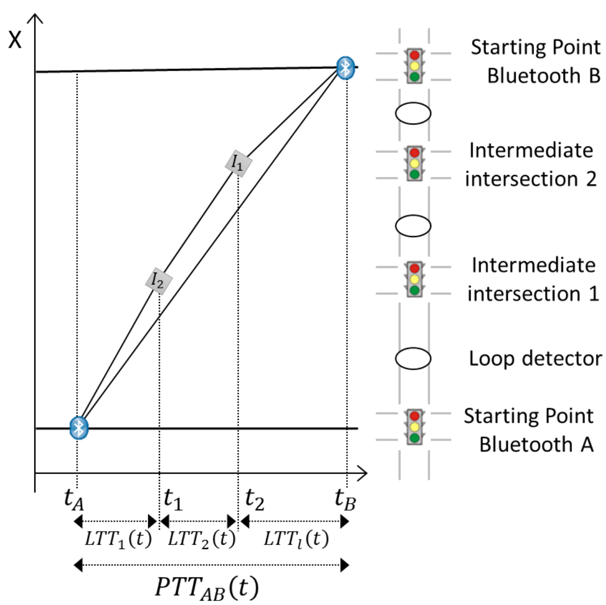


Figure 3. Reconstruction of travel time

We use link-based travel time, in which traffic conditions (speed reported by loop detectors) are assumed to be constant. The vehicle speed is considered linearly increasing or decreasing between intersections.

A serious challenge in traffic data is that the typical scale of some traffic patterns, such as the wavelength of stop-and-go waves, is similar to the spacing of stationary detectors. Consequently, important dynamical features may be lost in the interpolation process, and even entirely spurious patterns may be reconstructed [19].

The switch between free and congested traffic is then managed by an adaptive speed filter. A smoothing function performs two-dimensional interpolation to reconstruct the spatiotemporal traffic state from discrete traffic data. The adaptive weight factor $0 < W_s(t) < 1$ controls the superposition of the free and congested velocity fields and can be estimated as

$$\mathrm{W_s(t)} = \frac{\sum_1^l \mathrm{LTT_x(t)} - \sum_1^l \mathrm{LTT_x^f}}{\sum_1^l \mathrm{LTT_x^j} - \sum_1^l \mathrm{LTT_x^f}} \tag{6}$$

where $LTT_l^j$ denotes congested traffic operations and $LTT_l^f$ denotes free flow conditions from historical data between intersections. $LTT_x^s(t)$ is smoothed $LTT(t)$ of detector *x* at time interval *t*, estimated by combining the values for free and congested traffic:

$$\mathrm{LTT_x^s(t)} = \mathrm{W_s(t)LTT_x^j} + \left(1 - \mathrm{W_s(t)}\right)\mathrm{LTT_x^f} \tag{7}$$

The ratio of $LTT_x^s(t)$ is used to generate piece-wise link travel times $LTT_x(t)$:

$$\mathrm{LTT_x(t)} = PTT_{AB}(t) \times \frac{\mathrm{LTT_l^s(t)}}{\sum_1^l \mathrm{LTT_l^s(t)}} \tag{8}$$

### B. Travel Time Prediction

Support Vector Machines (SVMs), learning machines implementing the structural risk minimization inductive principle, is used to obtain good generalization on a limited number of learning patterns in travel time prediction. SVMs work by solving a constrained quadratic problem where the convex objective function for minimization is given by the combination of a loss function with a regularization term [20].

Traditional regression procedures are often stated as the processes deriving a function *f*(*x*) that has the least deviation between predicted and experimentally observed responses for all training examples. One of the main characteristics of Support Vector Regression (SVR) is that instead of minimizing the observed training error, SVR attempts to minimize the generalized error bound to achieve generalized performance. This generalization error bound is the combination of the training error and a regularization term that controls the complexity of the hypothesis space.

The approximate function is determined by a small subset of training samples called Support Vectors (SVs). A specific loss function is developed to make a sparseness property for SVR. In order to learn the non-linear relations by linear machines, selecting a set of non-linear features and rewriting

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the data in the new representation are needed, equivalent to applying a fixed non-linear mapping of the input space to a feature space in which the linear machine can be used. In SVR, the input *x* is first mapped onto a *m*-dimensional feature space using some fixed (nonlinear) mapping. Then, a linear model is constructed in this feature space. Using mathematical notation, the linear model in the feature space, $f(\mathbf{x},\omega)$, is given by

$$f(\mathbf{x},\omega)=\sum_{j=1}^{m}\omega_j g_j(\mathbf{x})+b \tag{9}$$

where $g_j(\mathbf{x}), j=1,\dots,m$ denotes a set of nonlinear transformations, and *b* is the "bias" term. Often the data are assumed to be zero mean, so the bias term in (9) is dropped.

The quality of estimation is measured by the loss function $L(y, f(\mathbf{x},\omega))$. The SVR uses a new type of loss function called $\varepsilon$-insensitive loss function

$$L_\varepsilon(y, f(\mathbf{x},\omega))=\begin{cases}0 & if\ |y-f(\mathbf{x},\omega)|\le\varepsilon\\ |y-f(\mathbf{x},\omega)|-\varepsilon & otherwise\end{cases} \tag{10}$$

The empirical risk is

$$R_{emp}(\omega)=\frac{1}{n}\sum_{i=1}^{n}L_\varepsilon(y_i, f(\mathbf{x}_i,\omega)) \tag{11}$$

Note that $\varepsilon$-insensitive loss coincides with least-modulus loss and with a special case of robust loss function when $\varepsilon$ =0. Hence, we shall compare prediction performance of SVM (with proposed chosen $\varepsilon$ ) with regression estimates obtained using least-modulus loss ( $\varepsilon$ =0) for various noise densities.

SVM regression performs linear regression in the high-dimension feature space using $\varepsilon$-insensitive loss and, at the same time, tries to reduce model complexity by minimizing $\|\omega\|^2$ . This can be described by introducing (non-negative) slack variables $\xi_i, \xi_i^*$ ( $i=1,..n$), to measure the deviation of training samples outside $\varepsilon$-insensitive zone. The SVR is formulated as minimization of the following objective function:

$$\min\quad \frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}(\xi_i+\xi_i^*) \tag{12}$$

$$\text{s.t.}\quad \begin{cases} y_i-f(\mathbf{x}_i,\omega)\le\varepsilon+\xi_i^*\\ f(\mathbf{x}_i,\omega)-y_i\le\varepsilon+\xi_i\\ \xi_i\ ,\xi_i^*\ge 0, i=1,\dots,n\end{cases}$$

This optimization problem can transformed into the dual problem, and its solution is given by

$$f(\mathbf{x})=\sum_{i=1}^{n_{SV}}(\alpha_i-\alpha_i^*)K(\mathbf{x}_i,\mathbf{x}) \tag{13}$$

$$\text{s.t. } 0\le\alpha_i^*\le C,\ 0\le\alpha_i\le C$$

where $n_{SV}$ is the number of Support Vectors (SVs) and the kernel function

$$K(x,z)=\left(c+\langle x,z\rangle\right)^d \tag{14}$$

In this study, polynomial kernel with *c* = 1, and *d* = 2 is used for prediction of link travel time (Fig. 3).

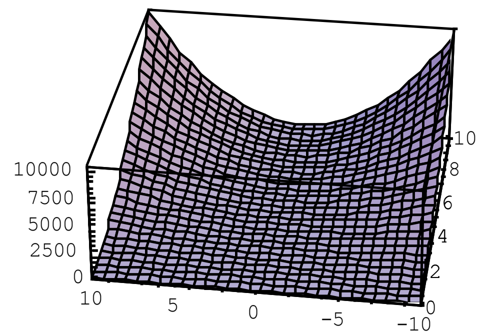


Figure 4. Instantaneous and Predicted Travel Times.

To handle fully dense quadratic optimizations in SVR, decomposition methods are designed. Unlike most optimization methods that update the whole vector α in each step of an iterative process, the decomposition method modifies only a subset of α per iteration. This subset, denoted as the working set B, leads to a small sub-problem to be minimized in each iteration. An extreme case is the Sequential Minimal Optimization (SMO) [21], which restricts B to have only two elements. Then, in each iteration one does not require any optimization software in order to solve a simple two-variable problem.

The model is applied to real world transportation network from the FHWA test data set [22]. The network consist of 4 intersections on 82nd street for afternoon peak hours (4:00 PM–6:00 PM) from 9/15/2012 to 11/14/2012. The data include following information:

- Phase and timing data consists of active calls and phasing information for four signals.
- Bluetooth data consists of travel times derived from matching MAC addresses that are captured by the Bluetooth readers between a pair of locations
- Loop detector data consists of speed on link between upstream and downstream.

In order to compare the performance measures before and after the field implementation, forty seven weekdays travel time need to be trained, after paring signal timing and reconstructing link travel time. The polynomial kernel function is used for SVR travel time prediction model. We examine the travel time of three links from the intersections of 82nd and Woodward to 82nd and Foster. Relative Mean

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Errors (RME), the ratio of difference between predicted error and actual travel time to the quantity, is calculated to evaluate prediction performance of the model, for 60 seconds interval. The results in Table I show the RME and RMSE of SVR for different travel distances over all the data points of the testing set. They show that the SVR predictor represent each temporal and spatial vehicle platoon in a feasible range. However, if penetration rate is higher, shorter interval with higher frequency of detection will be available and we can provide more accurate inputs for signal optimizations.

TABLE I. PREDICTION RESULTS

| | **RME** | **RMSE** |
|---|---|---|
| Link 1 (0.5mi) | 10.52% | 19.56% |
| Link 2 (0.6mi) | 9.84% | 17.94% |
| Link 3 (0.6mi) | 12.32% | 22.54% |

The optimized offset values were implemented on afternoon peak hours on 11/15/2012. The arterial outbound bandwidth is 29 seconds, and 25 seconds for the inbound. Arterial bandwidth efficiency is 21.16%, and bandwidth attainability is 63.74%, which means a fair progression according to the guidelines of bandwidth efficiency [23].

The existing field offset setting is {0, -24.9, -21.6, 4.6}, and its weighted total delay per cycle for each intersection is 183.8 seconds. In comparison, the optimized offset values were implemented and the best offset result is {0, -21.4, -21, -20.9} for four intersections, and the weighted total delay per cycle is 30.4 seconds. We should note that the above offset values are computed under the transformed time coordinates.

Table II compares the calculated travel time delays of both eastbound (from stop line of Boone to stop line of TH100) and westbound (from stop line of TH100 to stop line of Boone) based on different offset settings.

TABLE II. AVERAGE DELAY COMPARISION BEFORE AND AFTER

| | **Original (Before)** | **Optimized (After)** | **Change percentage** |
|---|---|---|---|
| Northbound average delay (seconds) | 784.8 | 678.4 | 13.6% |
| Southbound average delay (seconds) | 119.8 | 107.4 | 10.4% |

As we can see, both eastbound and westbound travel time delays are substantially reduced after the offset adjustment. On average, the northbound travel time delay with original offset (9/3/2009) is 784.8 seconds and it decreases to 678.4 seconds after optimization (9/14/2009), which is a 13.6% reduction. For southbound, average travel time delay with original offset is 119.8 seconds and it decreases to 107.4 seconds after optimization, which indicates a 10.4% reduction. As traffic condition is more congested (northbound), reduction of travel time delay is higher. Considering that the original offset setting was already optimized, the improvement is significant.

## V. CONCLUSION AND FUTURE WORK

In this paper, we proposed an application of Bluetooth technology to signal control by improving the quality of travel time prediction. Proposed method presents fair bandwidth progression efficiency and attainability, and lower delays than the current signal planning.

A number of possible future research directions exist. For example, the applicability of the proposed model is currently limited to through movement of traffic. A worthwhile research effort would be to generalize the model to the network level to obtain network-wide movements into signal controls. A challenging part of Bluetooth data is the small number of sample data. By using distribution of travel time data collected from each loop detector, Bluetooth data can be augmented. Accurate estimation of queue and arrival dynamics can be integrated for the optimal signal timing.

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