Placement of Roadside Equipment (RSE) in Connected Vehicle Environment for Travel Time Estimation

Jalil Kianfar
Ph.D. Candidate, Department of Civil and Environmental Engineering, University of Missouri, E2509 Lafferre Hall, Columbia MO 65211

Praveen Edara, Ph.D., P.E.*
Assistant Professor, Department of Civil and Environmental Engineering, University of Missouri, E3502 Lafferre Hall, Columbia MO 65211
Email: edarap@missouri.edu, Ph: (573) 882 1900, Fax: (573) 882 4784

Revised Submission Date: November 15th 2012
Word Count: 7674 (5924 text plus 1750 (5 figures and 2 tables))

* Corresponding author
ABSTRACT

Vehicle-to-Infrastructure (V2I) technology offers great potential in improving the safety and mobility in a transportation system. One mobility application is the travel time measurement in an urban road network. The presence of traffic control at intersections in an urban network makes it challenging for traditional traffic monitoring methods to provide accurate travel times. Several new technologies (e.g., Bluetooth) have been proposed to alleviate this problem. One of the features of V2I technology is probe vehicle data collection, where vehicles collect information such as their location and speed. The speed information can be used for travel time estimation. In this paper, one necessary and crucial aspect of travel time estimation using V2I technology is investigated. The paper proposes a methodology for determining the optimal placement of roadside equipment (RSEs) for travel time estimation in a V2I environment. A connected vehicle simulation test-bed of Boise, Idaho, was developed in the VISSIM traffic simulation software following the SAE J2735 standard. A hybrid performance measure, network coverage index, which combines travel time error and the number of links for which travel times are available was proposed. A Genetic Algorithm-based solution method was implemented in conjunction with the simulation test-bed to determine the optimal placement of different RSE deployments. The results indicate that the proposed methodology is capable of optimizing RSE locations in a V2I environment. Sensitivity analysis was also conducted by varying the market penetration rate and travel time estimation interval. The results indicated that higher penetration rates and bigger estimation intervals produced better coverage index values.
INTRODUCTION

Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) applications are new areas in the field of transportation. They provide a driving environment where each vehicle is fully connected to the other vehicles and to the infrastructure in its surrounding area. The goal of these applications is to improve safety and efficiency of a transportation system. While these applications offer a lot of opportunities, there are technical and legal issues that should be addressed before their real-world implementation.

The V2I and V2V applications are categorized into three main areas: safety, mobility and environmental applications (1). Each of these categories could be further divided into systems and subsystems. Traveler information systems are considered a part of mobility applications. They provide travelers with current or predicted travel times in the road network. The system delivers information to travelers through cell phone applications, variable message signs, websites, media outlets, and in-vehicle navigation units. Traveler information such as travel times are typically estimated by traffic management centers using various travel time estimation and prediction algorithms.

Traditionally, traffic detectors are used as the source of data for travel time estimation around the world. Traffic detectors are installed on freeways and arterials to measure traffic characteristics such as flow, speed, and occupancy (2). One common method of deriving link travel time from a point-based speed is to divide the link length by the speed. One major disadvantage of this method is the assumption that speed of vehicles remains the same throughout the link. If the link lengths are short or detectors are closely spaced such an assumption may not have a significant effect on the travel time estimate. However, a dense deployment of detectors is expensive not only in capital costs but also in maintenance costs. Another limitation of point-based travel time estimation is the difficulty in estimating travel times for arterial streets. Due to traffic signals and other forms of traffic control the travel time estimation for arterials is more complex than for freeways. Therefore, in recent years new methods have been proposed to estimate travel times by tracking cell phones on the network (3-4), by tracking Bluetooth devices on the roadway (5-7), by using toll collection data (8), automatic vehicle identification (AVI) (9-10), and vehicle signature analysis (11). Although promising, technologies such as cell phone and Bluetooth tracking require sufficient market penetration and also have privacy concerns.

In this paper, travel time estimation in an urban road network using the V2I technology is investigated. One feature of the V2I environment is probe vehicle data collection, where vehicles autonomously collect information such as their location and speed. This data is stored in vehicle OBU. The collected data is transferred wirelessly from vehicles to the system when a vehicle enters a RSE coverage range. RSEs are part of transportation infrastructure and can be installed at locations such as intersections or interchanges. The RSEs send and receive data to and from vehicles. The more number of RSEs installed in the network the frequency of reading the vehicles data will increase and less data is likely to be lost due to overwriting snapshots. Due to the budgetary constraints of deploying and maintaining RSEs state and local transportation agencies face the challenge of identifying the number and deployment locations of RSEs in a road network. The objective of this study is to propose a methodology to identify the optimal placement of RSEs in the network for the purpose of travel time estimation. To the best
of our knowledge, this is the first attempt to optimize the deployment of RSEs in a V2I environment. This research problem is different in nature with other detector placement or AVI reader placement problems where detectors only provide point measurements of speeds and a pair of AVI readers can only measure the travel time between readers. As a result, point detectors and AVI readers only provide the travel time for a segment or a route they are installed on. On the other hand, in a V2I environment RSEs continuously receive speed data from vehicles traversing multiple links on their path. Speed observations and other parameters are typically stored in the OBU for a limited time after which they will be overwritten by new observations after that time, if not transferred to a RSE.

A simulation test-bed in VISSIM microscopic simulation software was developed by following the SAE J2735 standard (12) connected vehicle probe vehicle data collection. The Society of Automotive Engineers (SAE) J2735 standard is developed to support the interoperability of transferring data in V2I and V2V applications, including traffic probe data collection. The standard is a series of “message sets, data frames and data elements” (12) for DSRC communications. A Genetic Algorithm-based solution method was implemented in conjunction with the simulation test-bed to determine the optimal placement of RSEs in a hypothetical urban road network in Boise, Idaho.

VEHICLE-TO-INFRASTRUCTURE (V2I) PROBE DATA

On-Board Unit (OBU), Roadside Equipment (RSE), and Dedicated Short-Range Communication (DSRC) are the three major elements in the V2I environment that are necessary for collecting probe data and for other V2I applications. Each element is briefly described next:

1) On-Board Unit (OBU): OBUs are installed in vehicles and record vehicle activity data in certain intervals; recorded vehicle activities are called snapshots. Snapshots include data such as speed, position, turn signal and brake status, airbag activation and etc; OBU memory size is limited and it can only store a limited number of snapshots. Total number of snapshots that can be stored is called buffer size.

2) Roadside Equipment (RSE): RSEs are installed at intersection, interchanges and other locations to provide communication interface to the vehicles. When a vehicle enters a RSE coverage area the information stored in OBU is transmitted to RSE and the OBU buffer will be cleared.

3) Dedicated Short-Range Communication (DSRC): DSRC is a wireless communication channel that is particularly designed for automotive and transportation applications.

Vehicle OBUs record three types of snapshots: periodic snapshots, start and stop snapshots, and event triggered snapshots. Periodic snapshots are recorded at regular intervals. When vehicle speed is greater than or equal to 60 mph, periodic snapshots are recorded at 20-second intervals. When vehicle speed is less than or equal to 20 mph, snapshots are recorded at 4-second intervals. For speeds between 20 mph and 60 mph, a linear approximation is used to identify the snapshot interval. Start and stop snapshots are recorded when i) a vehicle does not move (i.e., speed=0) for five seconds, and ii) when there is no record of vehicle stopping within a 15-second interval. When a stop snapshot is recorded, periodic snapshot is no longer recorded. A start snapshot is recorded when
the vehicle speed exceeds 10 mph. Event triggered snapshots are recorded when vehicle status elements change. Airbag activation is an example of an event-triggered snapshot.

**LITERATURE REVIEW**

This paper addresses the problem of identifying the optimal placing of RSEs in a network for travel time estimation using V2I data. Accordingly, three areas of interest are reviewed in this section: connected vehicle simulation, connected vehicle mobility, and optimization techniques for location analysis.

**Connected Vehicle Simulation**

In terms of connected vehicle simulation, there are very few studies that have developed a test-bed using commercial traffic simulation software. Dion et al. (13) developed a virtual test-bed for connected vehicles and evaluated the probe data generated in connected vehicle environment. They simulated the USDOT test-bed in Michigan in Paramics traffic simulation software and followed the SAE J2735 standard to collect data. They performed sensitivity analysis on effect of number of RSEs, RSEs communication range, OBU buffer size and snapshot generation interval and market penetration on the probe data. They also investigated the quality of link travel time estimates from connected vehicle probe data.

In another study Dion et al. (14) evaluated the issues related to usability of connected vehicle generated probe data based on current standards. They recommended several improvements to current probe data protocols. In terms of snapshot intervals, they recommended fixed-interval snapshots and preferably short intervals. In the current protocol snapshots are created based on vehicle speed. Also, the current protocol does not allow snapshots to be created while a vehicle is stopped. They advocated for a protocol that generates snapshots while vehicles are stopped, records link exit snapshots, and allows vehicles to continue uploading snapshots while they are in RSEs coverage range.

Shladover and Kuhn (15) investigated the quality of connected vehicle probe data for adaptive signal control, incident detection and weather condition monitoring systems. They used VISSIM to simulate approximately 10 km of SR-82 in Palo Alto and Mountain View in California. This corridor covers segments of California’s connected vehicle test-bed and includes 25 signalized intersections. Vehicle trajectories were recorded and processed based on the SAE J2735 standard. Market penetration was assumed to be 100%. They concluded the data collected based on current probe data protocol provides an acceptable representation of normal traffic conditions assuming 1 to 2 minute data latency is acceptable.

**Connected Vehicle Mobility Applications**

Connected Vehicle applications were formerly known as Vehicle Infrastructure Integration (VII) and IntelliDrive. Many researchers have applied the data that could possibly be provided by technologies similar to connected vehicles to address transportation problems. However, in majority of those studies the concepts of OBE, RSE, and collecting data based on SAE J2735 standard were not taken into account.
Oh et al. (16) developed “ubiquitous probe vehicle surveillance system (UBIPROSS)” that uses GPS and V2V communication to collect probe data. The probe data included vehicle travel time, speed and position. In the suggested framework, probe vehicle functions were to: 1) collect vehicle position data, 2) transfer the vehicle position data to nearby vehicles and receive nearby vehicles position data, and 3) transmit the collected data to the agents, such as roadside equipment unit (RSE) or traffic management center. Monte Carlo simulation was used to identify the values of parameters affecting system performance. Parameters such as the communication range, estimation interval, and market penetration rate were investigated. A 1.8 mile (3 kilometer) freeway segment was simulated and the result indicated that during normal traffic conditions travel time could be estimated with 5% average absolute relative error. One difference between UBIPROSS and the current paper is the resolution of probe data collection. UBIPROSS used a fixed 1-second resolution whereas the current study uses the SAE J2735 standard and treats resolution as a variable between 4 and 20 seconds. One other difference is that while Oh et al. (16) used a freeway segment to demonstrate their methods, the current study uses a downtown arterial network for optimizing RSE locations.

Rim et al. (17) developed a travel time estimation model that uses vehicles’ speed and coordinates provided by V2V and V2I to estimate lane-level travel times. The structure of model was based on concept of dynamically defined links and nodes. The vehicle trajectory data for a 4.6 mile (7.42 km) segment of highway in South Korea were obtained from VISSIM and used for travel time estimation. They found that with 20% or higher market penetration the mean absolute relative error of 6% to 8% is achievable.

Argote et al. (18) focused on estimating signalized arterials measures of effectiveness (MOE) assuming vehicle data could be provided by connected vehicle technology. They used NGSIM data with 0.1 second resolution to estimate queue length, average speed, average delay per unit distance, average number of stops and average acceleration noise. They concluded the minimum market penetration for accurate MOE estimation is not the same for all MOEs. The results indicate that average speed and average number of stops can be estimated accurately with market penetration of 50% or more. Although they analyzed the sensitivity of MOE estimates to market penetration they did not report using any protocol for creating snapshots and transferring the data.

Xu and Barth (19) developed travel time estimation models that utilize data from inter-vehicle communication systems. In the modeled inter-vehicle communication system every vehicle records its status data, calculates its travel time and transmits it to other vehicles. They studied three different models for travel time estimation and concluded that the type of travel time estimation algorithm can have a significant effect on the accuracy of output. The best model provided link travel time estimates with less than 10% error on 97% of network links. Li et al. (20) utilized VII collected data for arterial performance measurement. Average travel time was used as arterial MOE. Real-time inputs from point detectors (inductive loop detectors) and traffic signal controllers were combined with VII probe data.

Optimization Applications in Location Analysis

The problem of the placement of RSEs in a road network is not unique. It belongs to the broad field of location theory that deals with the placement of infrastructure facilities in a
given space by optimizing certain desired objectives (21). Operations research techniques are used to determine the optimal location of the desired facilities. Sherali et al. (22) proposed a linear mixed-integer programming formulation and a branch-and-bound solution to determine the optimal locations for automatic vehicle identification (AVI) readers for the purpose of providing roadway travel times. Yang and Zhou (23) proposed an integer linear programming model and a heuristic greedy algorithm to solve for the optimal traffic count locations in a network for the purpose of providing better origin-destination trip matrices. Ehlert et al. (24) also proposed a mixed integer programming formulation to optimize traffic count locations for providing origin-destination information. Chan and Lam (25) proposed a bi-level programming model to determine the appropriate detector density for minimizing both the travel time variance and the social cost of detectors. Kang et al. (26) combined genetic algorithm with GIS to develop a tool for optimizing highway alignments. Kim and Damnjanovic (27) applied the genetic algorithm to identify the optimal locations of smart garages. Edara et al. (28) identified the optimal location of traffic detectors on Virginia freeways by using genetic algorithm. Selmic et al (29) identify the optimal location of inspection facilities in a network by using the bee colony optimization (BCO).

**METHODOLOGY**

This study focuses on optimizing RSE locations for estimating travel times on links in a road network. Each link travel time is estimated and updated in \( t \) min intervals. Link travel time is estimated based on speed of vehicles in the past \( t \) minutes, available from V2I data. Vehicle snapshots (that include vehicle speed, coordinates, and timestamp) are stored in vehicle OBU according to the SAE J2735 standard. However, the collected data is not available for travel time estimation until it is transferred to a RSE. Figure 1 shows vehicle \( i \) traveling on link \( l \). Considering vehicle \( i \)'s travel path, data related to speed of vehicle \( i \) on link \( l \) will not be accessible until vehicle \( i \) passes by \( RSE \). As vehicle \( i \) continues on its path, depending on the distance between link \( l \) and \( RSE \), some of the snapshots recorded on link \( l \) might be replaced with new snapshots or might loose their usefulness for travel time estimation due to the long time gap between the record time and the upload time.

![FIGURE 1 Sample Network with RSEs](image-url)
Travel Time Estimation

Speed and location information of vehicles available from the uploaded snapshots are used to estimate link travel times. Snapshots are captured at certain intervals and during certain events \((I2)\). It is assumed that up to 30 snapshots could be stored in OBU. When a vehicle enters a RSE coverage range, the snapshots stored in the vehicle’s OBU are transferred to the RSE. Each snapshot contains information such as speed and location of the vehicle, the time snapshot was captured, and the time snapshot was transferred from OBU to RSE.

In order to estimate a link’s travel time, the available snapshots of vehicles traveling on the link during the estimation interval (e.g. past five minutes) are retrieved from the snapshots that had already been transferred to RSEs. Link travel time is estimated as follows:

\[
ETT_{l,j} = p \times L_l \left[ \sum_{n=1}^{C} \left( \frac{\sum_{t=1}^{T} (v_{n,t} \times y_{n,t,l})}{\sum_{t=1}^{T} y_{n,t,l}} \right) \right]
\]

where, \(ETT_{l,j}\) : estimated travel time of link \(l\) at time \(j\)
\(p\) : length of travel time estimation interval
\(L_l\) : length of link \(l\)
\(C\) : number of vehicles in the network
\(v_{n,t}\) : speed of vehicle \(n\) at time \(t\) available from uploaded snapshots database
\(y_{n,t,l}\) = \[\begin{cases} 1 & \text{if vehicle } n \text{ is at link } l \text{ at time } t \\ 0 & \text{otherwise} \end{cases}\]

Average absolute relative error (\(AARE\)) is a measure of effectiveness expressed as follows:

\[
AARE = \frac{\sum_{l=1}^{K} \sum_{t=1}^{T} \left( \alpha_{t,l} \times \frac{ETT_{l,t} - GTTT_{l,t}}{GTTT_{l,t}} \right)}{\sum_{l=1}^{K} \sum_{t=1}^{T} \alpha_{t,l}}
\]

where, \(ETT_{l,t}\) : estimated travel time of link \(l\) at time interval \(t\)
\(GTTT_{l,t}\) : ground truth travel time of link \(l\) at time interval \(t\)
\(K\) : number of links
\(T\) : number of travel time estimation intervals
\(\alpha_{t,l}\) = \[\begin{cases} 1 & \text{if } \beta_l > (0.9 \times T) \\ 0 & \text{otherwise} \end{cases}\]
\(\beta_l\) : number of available travel time estimates for link \(l\)

Travel time estimation might not be possible for some links at certain time intervals when snapshots of vehicles traveling on a link are overwritten or when snapshots are transferred with a long time gap. Also, link travel time estimation might not
be possible when there is not enough traffic flow on the link during a time interval. The parameter $\alpha_j$ takes into account such instances. In this study, only links that had travel time estimates for 90% or more estimation intervals were considered in the AARE computation.

**Optimization Problem**

The objective function, network coverage index, is a combination of the average absolute travel time error (AARE) and the number of links for which travel time estimates can be provided. The objective of this study is to find the optimal placement of RSEs in a road network that maximizes the network coverage index for a given RSE deployment (i.e., number of RSEs to be deployed). The optimization problem was solved using Genetic Algorithms (GAs). GAs were first developed by John Holland at the University of Michigan. Based on Darwin’s Theory of Natural Selection, GAs are structured, yet random, searches in which the survival of fittest criteria is used to proceed from one generation of solutions to the next (30). The new generation of solutions (on an average) is expected to perform better than the parent population because only the ‘good’ solutions from the parent population are allowed to participate in mating and producing offspring.

Each possible solution is considered a chromosome and chromosomes consist of genes. Thus, RSE deployment plans were coded as chromosomes where each gene represented the location of a RSE. It was assumed that RSEs were only installed at intersections. If a RSE was installed at an intersection the value of that gene would be set to 1 and otherwise it would be set to 0. The RSE deployment plan is represented as:

$$D_{j,k} = [y_{i,j,k}, \ldots, y_{i,j,k}, \ldots, y_{M,N,G}]$$ (3)

where, $D_{j,k}$: RSE deployment plan
- $i$: represents intersection $i$ in the network
- $j$: deployment plan number (chromosome number)
- $k$: generation number
- $M$: number of intersections in the network
- $N$: number of chromosomes in the generation
- $G$: number of generations
- $y_{i,j,k} = \begin{cases} 
1 & \text{if there is a RSE at intersection } i \text{ in deployment plan } j \text{ in generation } k \\
0 & \text{otherwise}
\end{cases}$

The fitness function, the network coverage index, is expressed as follows:

$$CI(D_{j,k}) = \frac{a_{j,k}}{AARE_{j,k}}$$ (4)

where, $CI(D_{j,k})$: coverage index for deployment plan $D_{j,k}$
- $a_{j,k}$: number of covered links for deployment plan $D_{j,k}$
- $AARE_{j,k}$: average absolute relative error for deployment plan $D_{j,k}$
A link is considered as ‘covered’ when V2I data is available for the link in 90% of the travel time estimation intervals. The initial population was generated randomly with each chromosome representing a possible plan of RSE deployment. Given a RSE deployment plan link travel times were estimated using the simulation model. The network coverage index was then computed from the travel times. Reproduction, crossover, and mutation operators are used to create the new generation. Roulette wheel selection method is used to select the chromosomes for reproduction, crossover and generation (30).

**SIMULATION TEST-BED**

A simulation test-bed of Boise, Idaho’s downtown network was developed in the VISSIM traffic simulation software. A screenshot of the test-bed is shown in Figure 2. The VISSIM COM feature was used to simulate V2I applications and GAs were implemented in MATLAB. Snapshots were created based on the SAE J2735 DSRC message set dictionary for traffic probes and operation. The test-bed was required for evaluating RSE deployment plans generated by the GAs. Link travel times were estimated in five-minute intervals and the fitness values were calculated.

Several assumptions were made in using GAs. The population size was assumed to be 10, the reproduction rate of 45%, crossover rate of 40%, and mutation rate of 15%, and the total number of generations was 15. The OBU buffer size was assumed to be 30. As previously mentioned, it was assumed that RSEs were only deployed at intersections. The market penetration was set to 100%.

The road network consisted of 152 links. Travel times were estimated for 108 links in the network (entry and exit links in the network were not included). Average length of these links is 389 feet (0.07 mile). The simulation period was 45 minutes with a 15-minute warm up period. The total network demand for the simulation period was 18,377 vehicles.

![FIGURE 2 Case Study Network](image-url)
RESULTS

The results of optimization for various RSE deployments are presented in this section. In the full network coverage scenario, 49 RSEs are deployed in the network. Figure 3 plots the improvement in the fitness value (network coverage index) versus the generation number. For illustration, eight sets of RSE deployments were investigated. These sets included 3, 6, 11, 14, 20, 24, 48, and 49 RSEs. Thus given the RSE set (i.e., number of RSEs to be deployed) the objective was to identify the optimal locations for the set.

Figure 3 shows the GA results for all eight sets. Two trends are evident from Figure 3: 1) the fitness value improved as the generation number increased, and 2) the maximum fitness value for a set increased as the set size increased (from 3 to 49). Both trends were expected and desirable. In most deployments, the fitness value improved significantly until 10 generations beyond which there was little improvement.

As previously explained a link was considered “covered” in a RSE deployment if a snapshot from that link was available in at least 90% of the travel time estimation intervals. Thus it is desirable to maximize the number of covered links in any RSE deployment. Table 1 presents the network coverage index value, number of covered links, and AAE averaged over all network links in columns 2, 3, and 4, respectively. Although the network AAE value did not vary much with the RSE deployment, an increasing trend was observed in the number of covered links with the increase in the number of RSEs deployed. For example, the coverage increased from 70% to 89% when the deployment increased from 3 RSEs to 14 RSEs.

Table 1 reported the AAE value averaged over all covered links in the network. The AAE values for individual links were also investigated. Table 2 shows the number (and percentage) of links belonging to each of the following four groups based on the link AAE value: 1) link AAE less than 1 second, 2) link AAE between 1 and 5 seconds, 3) link AAE between 5 and 10 seconds, and 4) link AAE greater than 10 seconds. The link AAE values for at least 57% of covered links were less than or equal to 5 sec in all RSE deployments. On the other hand, irrespective of the number of RSEs deployed optimally,
### TABLE 1 Link Coverage and Travel Time Error

<table>
<thead>
<tr>
<th>Number of RSEs</th>
<th>Coverage Index</th>
<th>Number of Covered Links (% Coverage)</th>
<th>Network Average Absolute Error $AAE$ (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>287</td>
<td>76 (70%)</td>
<td>5.98</td>
</tr>
<tr>
<td>6</td>
<td>326</td>
<td>82 (76%)</td>
<td>5.68</td>
</tr>
<tr>
<td>11</td>
<td>394</td>
<td>93 (86%)</td>
<td>5.26</td>
</tr>
<tr>
<td>14</td>
<td>395</td>
<td>96 (89%)</td>
<td>5.53</td>
</tr>
<tr>
<td>20</td>
<td>399</td>
<td>98 (91%)</td>
<td>5.68</td>
</tr>
<tr>
<td>24</td>
<td>411</td>
<td>102 (94%)</td>
<td>5.77</td>
</tr>
<tr>
<td>48</td>
<td>415</td>
<td>105 (97%)</td>
<td>5.82</td>
</tr>
<tr>
<td>49</td>
<td>413</td>
<td>105 (97%)</td>
<td>5.90</td>
</tr>
</tbody>
</table>

About 16% of covered links showed AAE values greater than 10 seconds. Three possible explanations are offered for this finding. First, long queues were observed on some of these links due to traffic signals that may have contributed to the higher AAE values. Second, the traffic volume on some of the links was low, thus not having sufficient sample size to estimate travel times. Third, in the current SAE standard when a vehicle stops, no periodic snapshot will be recorded until the vehicle speed exceeds 10 mph. Previous research has shown that this limitation affects travel time accuracy (13-14).

### TABLE 2 Frequency of Link Travel Time Estimation Error

<table>
<thead>
<tr>
<th>Number of RSEs</th>
<th>Frequency (and Percentage) of Link Average Absolute Error ($AAE$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>link $AAE &lt;=1$ sec</td>
</tr>
<tr>
<td>3</td>
<td>11 (15%)</td>
</tr>
<tr>
<td>6</td>
<td>12 (15%)</td>
</tr>
<tr>
<td>11</td>
<td>17 (18%)</td>
</tr>
<tr>
<td>14</td>
<td>16 (16%)</td>
</tr>
<tr>
<td>20</td>
<td>18 (18%)</td>
</tr>
<tr>
<td>24</td>
<td>14 (14%)</td>
</tr>
<tr>
<td>48</td>
<td>16 (15%)</td>
</tr>
<tr>
<td>49</td>
<td>16 (15%)</td>
</tr>
</tbody>
</table>

Sensitivity analysis was conducted with respect to the market penetration rates and travel time estimation intervals. First, four different market penetration rates, 20%, 50%, 80%, and 100%, were investigated to analyze their effect on RSE placement and coverage index. Four sets of RSE deployments were analyzed: very low (3 RSEs), low (11 RSEs), medium (24 RSEs), and high (48 RSEs). The convergence of coverage index values in GAs for all market penetration rates are shown in Figure 4. The results were intuitive in that for each set of deployed RSEs the coverage index improved as market penetration increased. The magnitude of improvement was greater when the rate increased from 20% to 50% than when it increased from 50% to 80% or 80% to 100%, thus indicating a non-linear relationship between the improvement in fitness value and the market penetration rate. One other trend can be inferred from Figure 4. The improvement in fitness value from early generations to later generations was found to be...
higher in low market penetration rates compared to high market penetration rates, especially when the RSE deployment is low.

The effect of travel time estimation interval on the fitness value was also investigated. Four different interval sizes, 30 sec, 1 min, 5 min and 15 min, were evaluated for three RSE deployments - 11 RSEs, 24 RSEs, and 48 RSEs. The results of GAs are shown in Figure 5. From the figure it can be inferred that the fitness values improved as the interval size increased from 30 sec to 15 min for all deployments, except for 48 RSEs where the fitness values of 5 min were slightly better than the 15 min values. One reason for this trend is that larger interval sizes produce more snapshot samples and thus improve the accuracy of travel times. The fitness values for large interval sizes, 5 min and 15 min, for all three sets of deployments converged around generation 14 to values very close to each other. Thus, if there is a hard constraint on the number of RSEs that can be deployed in a network an agency can improve the network travel time estimation by increasing the interval size to 5 min or 15 min.

FIGURE 4 Effect of Market Penetration Rate on Coverage Index

FIGURE 5 Sensitivity Analysis of Travel Time Estimation Interval
CONCLUSIONS

This paper proposed a methodology for identifying the optimal placement of RSEs for link travel time estimation in a connected vehicle environment. A hybrid performance measure, network coverage index, which combines travel time error and the coverage of links, was optimized for various RSE deployments. The optimization problem was solved with Genetic Algorithm. The methodology was illustrated for a case study of an urban area during peak period using a simulation test-bed. The results indicate that the proposed methodology is capable of optimizing RSEs in a V2I environment. The developed test-bed can be easily used to study other mobility applications of V2I. In most RSE deployments, the fitness value improved significantly until 10 generations beyond which there was little improvement.

An increasing trend was observed in the number of covered links with the increase in the number of RSEs deployed. For example, the coverage increased from 70% to 89% when the deployment increased from 3 RSEs to 14 RSEs. The network AAE value did not vary much with the RSE deployment. Investigation into the link-level AAE values revealed that the AAE values for at least 57% of covered links were less than or equal to 5 sec in all RSE deployments. And, regardless of the number of RSEs deployed, about 16% of covered links showed AAE values greater than 10 seconds. Possible reasons for this finding include: existence of queues on these links, insufficient sample sizes due to low traffic volumes on some of the links, and in the current SAE standard when a vehicle stops, no periodic snapshot will be recorded until the vehicle speed exceeds 10 mph thus affecting the sample size.

Sensitivity analysis with respect to market penetration rate and travel time estimation interval was also carried out. Four different market penetration rates of 20%, 50%, 80%, and 100% were investigated to analyze their effect on RSE placement and coverage index. Four sets of RSE deployments were analyzed: very low (3 RSEs), low (11 RSEs), medium (24 RSEs), and high (48 RSEs). The findings were intuitive in that for each set of deployed RSEs the coverage index improved as market penetration increased. The results indicated a non-linear relationship between the improvement in fitness value and the market penetration rate. The improvement in fitness value from early generations to later generations was found to be higher in low market penetration rates compared to high market penetration rates, especially when the RSE deployment is low.

The effect of travel time estimation interval on the fitness value was also investigated. Four different interval sizes, 30 sec, 1 min, 5 min and 15 min, were evaluated for three RSE deployments -11 RSEs, 24 RSEs, and 48 RSEs. The results indicated that larger interval sizes produce more snapshot samples and thus improve the accuracy of travel times. For interval sizes of 5 min and 15 min, the optimal performances for all three sets of RSE deployments were close to each other. Thus, if the number of RSEs that can be deployed is limited (e.g., due to a budgetary constraint) an agency can improve the network travel time estimation by increasing the travel time estimation interval size to 5 min or 15 min.

There are some natural extensions of the work presented in this paper. Future research could focus on: 1) using a different case study with different traffic patterns, and geometrics, for example a freeway network, 2) other solution methods for solving the
optimization problem, 3) objective function could include other connected vehicle
applications in addition to travel time estimation, and 4) alternate travel time estimation
methods.

ACKNOWLEDGMENT

Authors would like to thank Chen Chen of University of Missouri for her help in
validating the connected vehicle simulation test-bed.

REFERENCES

and Innovative Technology Administration, U.S. Department of Transportation, April
30, 2010.

(2) Shen, L., and M. A. Hadi. Estimation of Segment Travel Time Based on Point Traffic
Detector Measurements. In *TRB 88th Annual Meeting Compendium of Papers*. DVD-
ROM. Transportation Research Board of the National Academies, Washington, D.C.,
2009.

Monitoring Using Cell Phones: A Case Study in Rome. *IEEE Transactions on

Evaluation of Traffic Data Obtained via GPS-enabled Mobile Phones: The Mobile
Century Field Experiment. *Transportation Research Part C: Emerging Technologies*,

(5) Haseman, R. J., J. S. Wasson, and D. M. Bullock. Real-Time Measurement of Travel
Time Delay in Work Zones and Evaluation Metrics Using Bluetooth Probe Tracking.
In *Transportation Research Record: Journal of the Transportation Research Board*,
No. 2169, Transportation Research Board of the National Academies, Washington,

(6) Click, S. M., and T. Lloyd. Applicability of Bluetooth Data Collection Methods for
Collecting Traffic Operations Data on Rural Freeways. In *TRB 91st Annual Meeting
Compendium of Papers*. DVD-ROM. Transportation Research Board of the National

(7) Tsubota , T., A. Bhaskar, E. Chung, and R. Billot. Arterial Traffic Congestion
Analysis Using Bluetooth Duration Data. In *Australasian Transport Research Forum
2011 Proceedings*. 28 - 30 September 2011, Adelaide, Australia

(8) Faouzi, N.-E.El., R. Billot, S. Bouzebda. Motorway Travel Time Prediction Based on
Toll Data and Weather Effect Integration. *IET Intelligent Transport Systems*, Vol. 4,


