Impact of Vehicular Communication Performance on Travel Time Estimation in Urban Areas

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Abstract. Increasing traffic demands in urban agglomerations lead to a variety of traffic challenges which are reflected in increasing travel times, numbers of stops and pollutant emissions. One of the main challenges in order to counteract these negative effects is the exact determination or estimation of travel times, which is a basic requirement for each traffic control method, especially at urban intersections. In this paper, we present a travel time estimation (TTE) approach for urban areas based on vehicular communication. The impact of communication parameters such as transmission range, message generation rate and penetration rate on the quality of the TTE is analyzed using simulations. For this purpose, the performance of the vehicle-to-infrastructure-based travel time estimation (V2I-based TTE) is compared to a perfect TTE provided by the simulation platform. The results show that, while the penetration rate and the transmission range significantly affect the TTE accuracy, a message generation rate of 1 msg/s should be sufficient if at least 10 % of vehicles are equipped.

Keywords: vehicular communication, vehicle-to-infrastructure, travel time estimation

1 INTRODUCTION

In the past decades, increasing traffic demands in urban agglomerations have created a variety of traffic challenges that are reflected in increasing travel times, numbers of stops and pollutant emissions. In situations where traffic demand exceeds available capacities and urban road infrastructure presents a bottleneck, dynamic traffic management strategies, which adapt to traffic conditions, can improve traffic efficiency and thus help to meet these challenges.

Urban traffic mainly depends on the influence of junctions and signals, as in urban areas, traffic infrastructure components like traffic lights ensure equity between traffic participants by considering differing intensities of traffic flows. While traffic flows in
urban road networks significantly vary with respect to different network segments and times of the day, conventional traffic management provides simple strategies for traffic signals that only cover average traffic flows. Such strategies are not suited for traffic densities which significantly deviate from these averages. However, real-time optimization of urban intersection capacities can be achieved by continuously adapting traffic signal control systems to current traffic conditions. The main challenge in this context is the exact determination or estimation of the actual traffic conditions, which is a basic requirement for dynamic traffic management. In this paper, we focus on accurate estimation of travel time.

Travel time estimation is usually realized using stationary traffic detectors, e.g. magnetic loop detectors. The installation of these stationary detectors is associated with significant expense, especially if larger road networks shall be covered instead of single sections. In this context, wireless vehicular communication based on IEEE 802.11 Wireless LANs, known as ETSI ITS-G5 [1] in Europe (see section 2.1), presents an interesting alternative. European standardization has paved the way for a market introduction of these systems, which is planned for the next few years by major OEMs.

Periodic transmission of status messages by vehicles equipped with ITS-G5 to Roadside Units (RSUs) which in turn forward these messages to a Traffic Management Center (TMC) for centralized analysis, could allow travel time estimation even for low penetration rates, i.e. if few vehicles are equipped. In this paper, we study the capabilities of a traffic state estimation approach based on ITS-G5 vehicle-to-infrastructure (V2I) communication, which allows the derivation of section-specific travel times, using simulations. Furthermore, we focus on the effects of several communication parameters (message generation rate, transmission power, penetration rate) on the performance of the travel time accuracy.

In the last few years, several research contributions have addressed similar concepts related to travel time estimation and/or traffic efficiency improvement based on wireless communication. While Schumacher et al. [2] follow a similar approach regarding vehicular communication, they focus on traffic efficiency improvement using a lane merging assistance application in a freeway scenario. A simulation study for urban traffic state estimation using mobile phones equipped with Assisted GPS (A-GPS) is presented by Tao et al. [3]. Similar to our concept, vehicles send position probes to a central unit for section-specific calculation of average speeds. Vehicular communication, however, is not explicitly simulated, but statistical positioning errors are added artificially.

Decentralized approaches for traffic state estimation based on vehicle-to-vehicle (V2V) communication are presented by Wedel et al. [4], Bauza et al. [5] as well as Garelli et al. [6]. Vehicle-generated messages indicating the vehicle’s average section speed are used by Wedel et al. [4] to perform re-routing in case of congestion based on an adaptation a Dijkstra algorithm’s section weights. In their simulation study using an urban scenario, the authors focus on the rerouting functionality, but do not evaluate the quality of the traffic state estimation. In [5], vehicles report local
traffic density estimates and their current speed to their neighbourhood in a freeway scenario, and fuzzy logic is used to derive traffic conditions. The concept is evaluated using simulations, but the effects of partial penetration or other parameters are not discussed. Garelli et al. [6] also present an interesting approach for V2V-based traffic density estimation using POLL- and REPLY-messages from which traffic density can be inferred since the road network is known. Their simulations show a good fit with actual traffic density, but the authors assume that either all vehicles are equipped with communication devices or the penetration rate in the target area has to be known, which might be hard to realize.

The rest of this paper is structured as follows: In section 2, we explain the background and concepts behind our approach from the perspectives of vehicular communication and V2I-based travel time estimation. In section 3, our simulation study investigating the impact of vehicular communication performance on travel time estimation is presented by introducing the simulation methodology first and illustrating the results afterwards. A short conclusion completes the paper in section 4.

2 BACKGROUND AND CONCEPTS

This section describes the basic concepts behind our work. We first present the vehicular communication model which has been utilized for the simulation-based studies presented in section 3. Subsequently, we describe our approach used to determine the mean travel time on each section in the simulated network.

2.1 Vehicular Communication

Vehicular communication involves both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure communication (V2I) in vehicular ad hoc networks (VANETs). VANETs open up a new dimension of innovative applications, which have great potential to increase safety and comfort for the driver in the future. One such application is related to the use of V2I communication in order to improve road traffic state estimation, which is accomplished by infrastructure sensors today. However, the deployment of VANETs involves many challenges which have to be dealt with. These include, but are not limited to, the highly dynamic topology of vehicular networks (in contrast to typically static Wireless LANs), restricted availability of line of sight communication, severe multipath propagation (especially in urban and ultra-urban environments), and the required number of equipped vehicles to ensure acceptable traffic state estimation. Also, the wireless channel limits the reliability and capacity achievable in practice. These issues need to be taken into account as they are inherent to IEEE 802.11 Wireless LANs, which constitute the technological basis for VANETs.

In this work, in order to analyze the impact of vehicular communication performance on urban travel time estimation, simulations rely on the abstract communication model presented in our previous work [7], which reflects the ETSI ITS-G5 European standard for vehicular communication in the 5.9 GHz frequency band. ITS-G5 is based on IEEE 802.11, but contains several modifications specific to VANETs, for
example to allow communication without prior association or authentication with a Basic Service Set (BSS). Furthermore, our simulations model the exchange of Cooperative Awareness Messages (CAMs) between vehicles and Roadside Units (RSUs), which creates mutual awareness between nodes [8]. For this purpose, each vehicle periodically broadcasts CAMs, which contain status information such as position, speed, and driving direction, so that the presence of neighboring vehicles can be detected and current traffic conditions, in terms of travel time, can be estimated without the need for any additional traffic detectors.

2.2 Travel Time Estimation

As traffic load typically varies strongly throughout the day, an adaptation of traffic management according to the actual demand is essential, especially in urban areas. Hence, the availability of detailed information about actual travel times is a fundamental requirement for dynamic traffic management approaches within urban areas. This information is traditionally gathered using stationary traffic detectors like magnetic loop detectors, roadside radar or infrared detectors and cameras. While in the simplest case, only the number of vehicles is measured, additional data like location and speed of vehicles can be beneficial for travel time estimation.

Next generation dynamic traffic management can rely on vehicles and infrastructure being able to communicate with each other, allowing the exchange of status data which is relevant for the continuous determination of the actual traffic state. Within the work presented here, the capabilities of communicating vehicles are used for travel time estimation. The collection of vehicle-generated CAMs by RSUs and forwarding of these messages to a traffic management center (TMC) enables the measurement of travel times on a road section. The mean travel time on each road section is computed in discrete time intervals (e.g. 5 minutes) according to the following V2I-based TTE algorithm:

1. For each vehicle $i$, collect the timestamps $t_{in,i}$ and $t_{out,i}$ from the received CAMs, which indicate that vehicle $i$ has just entered or left a given road section, respectively. These timestamps correspond to the time when the first/last CAM originating from the given section was sent.

2. Compute the current mean travel time $T_{V2I}$ that vehicles will experience when traversing a given road section:

   \[
   T_{V2I} = \frac{1}{n} \sum_{i=1}^{n} t_{out,i} - t_{in,i} ,
   \]

   where $n$ is the number of vehicles tracked on the section during the time interval currently considered.

While the mean travel time $T_{ref}$, which is directly provided by the traffic simulator, is assumed to be exact and error-free, the V2I-determined mean travel time $T_{V2I}$ can be error-prone, as schematically illustrated in figure 1. This is attributable to delays (induced, e.g., by the message generation interval), insufficient radio coverage or packet loss caused by signal fading. $d_{in}$ and $d_{out}$ indicate the distance between the
location where the first/last CAM was sent and the beginning/end of the section and thus represent the distance offset induced by above mentioned effects.

![Figure 1: Relations between $T_{V2I}$, $T_{ref}$, $d_{in}$, and $d_{out}$](image1.png)

Figure 1: Relations between $T_{V2I}$, $T_{ref}$, $d_{in}$, and $d_{out}$.

Taking into account that the timestamps $t_{in}$ and $t_{out}$ correspond to the first and last CAM that was sent from a specific section, these timestamps may deviate from the points in time when the vehicle actually entered or left the section. Therefore, considering the speed of the vehicle as well as $d_{in}$ and $d_{out}$, the timestamps $t_{in}$ and $t_{out}$ can be adjusted by extrapolation. This extrapolation is expected to create a higher level of accuracy by reducing the gap between the measured travel time and the reference travel time. Note that the error-free reference travel time is obtained from detectors immediately installed at section endpoints.

Hence, for each pair of timestamps $t_{in}$ and $t_{out}$, the corresponding extrapolated timestamps $t_{in,ext}$ and $t_{out,ext}$ can be calculated as

$$t_{in,ext} = t_{in} - \frac{d_{in}}{v},$$

$$t_{out,ext} = t_{out} + \frac{d_{out}}{v_{mean}},$$

where $v$ denotes the vehicle’s instantaneous speed at the moment of message generation and $v_{mean}$ the vehicle’s average speed ($v, v_{mean} > 0$) on the given section.

Figure 2 illustrates the time adjustment obtained using the extrapolation method, which virtually shifts $t_{in}$ and $t_{out}$ to the points in time when the vehicle actually entered or left the section.

![Figure 2: Extrapolation of received timestamps.](image2.png)
3 PERFORMANCE EVALUATION

In this chapter, we evaluate the impact of communication parameters on the performance of urban travel time estimation based on V2I-communication. Specifically, we evaluate the accuracy of our V2I-based TTE by comparing its results to exact, error-free values which are provided by the utilized traffic simulator. Before presenting and discussing the results obtained from our analysis, we describe the simulation setup and define the main performance metrics used to evaluate the results.

3.1 Simulation Methodology

In this paper, both the V2I-based TTE model and the V2I communication model were implemented using the traffic simulation software AIMSUN and its API [9]. The AIMSUN API module allows us to model the behaviour of every single vehicle and the interaction between them. This is essential for vehicular communication simulation, as accurate wireless radio propagation modeling requires precise knowledge about positions of the communication entities. Our simulations assume perfect accuracy of the position data which is provided by the vehicles.

To develop and test the proposed TTE model, we have selected a test scenario, located in the southern city center of Hannover, Germany, which includes real traffic demands that have been empirically determined in previous studies. As the scenario’s traffic conditions include significant congestion during peak hours, the test scenario is suitable to assess how vehicular communication can effectively improve traffic management. Furthermore, the scenario was configured using real traffic light control programs which are currently in operation.

Every major intersection in the scenario is equipped with a RSU. Embedded in each RSU, the V2I communication system allows reception of CAMs from surrounding vehicles as well as forwarding of the corresponding status data to the TMC. As mentioned in section 2.2, the traffic information collected by RSUs allows the TMC to estimate the current travel time on different sections of the scenario.

<table>
<thead>
<tr>
<th>Table 1: Simulation setup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated time</td>
</tr>
<tr>
<td>Location of road network</td>
</tr>
<tr>
<td>Section speed limit</td>
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<tr>
<td>Number of RSUs</td>
</tr>
<tr>
<td>Transmission power [dBm]</td>
</tr>
<tr>
<td>Reliable transmission range [m]</td>
</tr>
<tr>
<td>CAM generation rate [msg/s]</td>
</tr>
<tr>
<td>Penetration rate [%]</td>
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</tbody>
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To investigate the influence of communication parameters on the accuracy of the V2I-based TTE, three input parameters are varied within the simulation setups:
transmission power, CAM generation rate, and the ratio of equipped vehicles to the total number of vehicles, i.e., the penetration rate. A summary of the most important simulation parameters is presented in table 1.

For a reasonable interpretation of results, we have classified the sections under investigation into two main classes: Class 1 comprises all sections which are connected to only one intersection equipped with a RSU (sections at the scenario borders), class 2 represent those sections which are located between two intersections equipped with a RSU, as shown in figure 3. This difference has to be considered in the context of result interpretation, as it affects radio coverage.

![Figure 3: Graphical representation of different section classes.](image)

To evaluate the performance of the V2I-based TTE, the following performance metrics were evaluated within the simulations:

**Normalized mean travel time error** ($\Delta_T$): This metric is calculated using the ratio of average V2I-determined mean travel time $T_{V2I}$ to the exact, error-free mean travel time $T_{ref}$, which is directly provided by the traffic simulator. A small normalized mean travel time error $\Delta_T$ corresponds to a high accuracy of the V2I-based TTE. It is defined by:

$$\Delta_T = 1 - \frac{T_{V2I}}{T_{ref}}.$$  

Negative values of $\Delta_T$ correspond to an overestimation of the V2I-determined travel time, a value of zero corresponds to a perfect agreement between the TTE given by fixed infrastructure sensors and the V2I-based approach.

**Mean distance offset** ($d_{off}$): This metric represents, as explained in Section 2.2, the distance offset induced by the V2I-based TTE approach, which obviously has an influence on the accuracy of the measured travel time. High packet generation rates are expected to result in low mean distance offsets $d_{off}$, indicating high accuracy. Moreover, this distance depends on the vehicle’s mean speed. The mean distance offset is defined as

$$d_{off} = d_{in} + d_{out}.$$  

### 3.2 Simulation Results and Evaluations

In this section, we present the results of our simulation study, which investigates the capabilities of the presented travel time estimation approach, aiming at the derivation of section-specific travel times. We focus on the effects of several communication parameters (message generation rate, transmission power, penetration rate) on the
travel time estimation accuracy. The presented performance metrics, normalized mean travel time errors as well as mean distance offsets, were calculated for 5-minute intervals and averaged over all samples and sections. In order to ensure statistical validity of the results, for all figures in this section, each data point represents the average of 10 simulation runs with different random seeds and 1 hour simulated time per run, including 95 % confidence intervals.

3.2.1 Impact of transmission power and penetration rate

The choice of transmission power is expected to have a significant impact on travel time estimation performance, as it directly affects the achievable transmission range. Our simulations rely on the probabilistic propagation model outlined in [7], which combines Friis’ Free Space Path Loss Model with the Nakagami-m distribution ($m = 3.0$) to model signal fading. Assuming a receiver sensitivity of -85 dBm, the model provides the probability that a transmitted message can be successfully decoded by a receiving node at a specific distance $d$ from the transmitter, denoted as reception probability $P_{\text{succ}}(d)$. Note that the current version of the implemented model considers packet loss due to signal propagation aspects (path loss and fading), but does not include loss caused by packet collisions. This is an acceptable simplification as only low network load is created by the V2I-based TTE approach.

Figure 4 depicts the reception probability as a function of the distance between transmitter and receiver for different transmission power values. It is apparent that the reception probability decreases with increasing distances. Higher transmission power values result in increasing transmission ranges. Since section lengths in our scenario range from 100 m to 600 m, near-complete section coverage is obtained for a transmission power of 23 dBm, as $P_{\text{succ}}(d = 600 \text{ m}) > 0.91$ in this case, while full coverage for all sections is obtained for a transmission power of 33 dBm, where $P_{\text{succ}}(d = 600 \text{ m}) > 0.999$.

In the following set of simulation results, transmission ranges were altered by varying transmission power configuration values between 5 dBm and 33 dBm. Furthermore, different penetration rates were investigated. The results presented in this subsection include a fixed CAM generation rate of 2 msg/s and no extrapolation (see section 2.2) was used. Figure 5 shows the normalized mean travel time errors with respect to the configured penetration rate. Lower absolute values of the normalized mean travel time error refer to a better accuracy of the V2I-based TTE. Note that for class 1 (see figure 5, left diagram) sections, a penetration rate of 5 % can provide comparable...
performance to a system where each vehicle is equipped with a communication system (100 % penetration rate).

![Figure 5: Normalized mean travel time errors ($\Delta_T$) for different transmission power values and penetration rates on class 1 sections (left) and class 2 sections (right).](image)

However, at lower penetration rates, the travel time may be slightly overestimated ($\Delta_T < 0$). This can probably be explained by a randomly selected portion of equipped vehicles suffering from an additional travel time increase due to a red phase at the end of a section. Furthermore, a pronounced difference can be observed if a transmission power of 5 dBm is used, which provides significantly underestimated travel times ($\Delta_T > 0.15$). This is caused by the fact that the transmission range is not large enough to cover the entire road section. Considering this fact, simulation results confirm the assumption that transmit power does not have a significant impact on the accuracy of travel time estimation for class 2 sections (see figure 5, right diagram), as the transmission range only has to cover half the section length in this case.

![Figure 6: Mean distance offsets ($d_{off}$) for different transmission power values and penetration rates on class 1 sections (left) and class 2 sections (right).](image)

Figure 6 shows mean distance offsets for different transmission powers and penetration rates. We can see that for class 1 sections (see figure 6, left diagram), higher transmission power values result in smaller mean distance offsets. In addition,
it can be observed that the penetration rate has no significant impact on mean distance offsets. For class 2 sections (see figure 6, right diagram), neither the transmit power nor the penetration rate have an impact on the resulting mean distance offsets. This can be explained by the fact that both start and end of the section allow reliable transmission of CAMs to RSUs due to the availability of RSUs at both intersections.

At this point, one can conclude that the low absolute values of normalized mean errors ($\Delta_T < 0.05$) and mean distance offsets ($d_{off} < 7\ m$) for both class 1 and 2 sections indicate a very good performance of the V2I-based TTE in most cases, i.e. for a transmission power of at least 15 dBm.

### 3.2.2 Impact of CAM generation rate

The points in time when the first and last CAM on a specific section are sent depend on the current speed of the vehicle and the CAM generation rate. Thus, it can be expected that the CAM generation rate significantly influences the results of the travel time estimation. For this reason, while the results presented above include a fixed generation rate of 2 msg/s, we investigate the effects of different generation rates on the travel time estimation results in this subsection.

Assuming a fixed transmission power of 15 dBm, figure 7 shows normalized mean travel time errors with respect to six different generation rates between 0.2 and 8 msg/s and two different penetration rates, 10 and 100%, on class 1 (left diagram) and class 2 (right diagram) sections. Furthermore, we evaluate the effects of the extrapolation (see section 2.2) on the results of the V2I-based TTE approach by comparing normalized mean travel time errors resulting from application and non-application of extrapolation.

Obviously, higher message generation rates create a higher probability of a message being sent immediately at the start or end of the section. Therefore, for both approaches, we note that the normalized mean travel time errors decrease when the message generation increase, which indicates more accurate travel time estimation.
As expected, extrapolation leads to performance improvements, since this method virtually shifts the collected timestamps indicating a vehicle entering or leaving an intersection to the section endpoints, as explained in section 2.2. For class 2 sections, there is no significant improvement due to the perfect radio coverage at both section ends for a transmission power of at least 15 dBm. However, a performance degradation caused by the extrapolation approach can be identified for a message generation rate of 0.2 msg/s (see figure 7, right diagram). In case of a severely congested section, the vehicle’s actual speed at the moment of message generation, which is used for travel time extrapolation, may become very low, which leads to an overestimation of the travel time and hence to a degraded accuracy of the traffic state estimation.

4 CONCLUSIONS AND OUTLOOK

In this paper, we have presented a travel time estimation method for urban areas based on vehicular communication. Altogether, the simulation results indicate a very good performance of the V2I-based travel time estimation approach. Especially for road sections offering full radio coverage, simulation results show a very good agreement between error-free travel times provided by the traffic simulator AIMSUN and travel times computed by our V2I-based travel time estimation algorithm. If a simple extrapolation of received timestamps is used, the maximum deviation between both methods is not higher than 7 %, even for low penetration rates, transmission powers and message generation rates. Results also show that, while the penetration rate and the communication range significantly affect the travel time estimation accuracy, a packet generation rate of one packet per second should be sufficient if at least 10 % of vehicles are equipped.

In further studies, the impact of frame collisions and scalability aspects, especially in urban vehicular networks, has to be analyzed using network simulations. For this purpose, a V2I-based travel time estimation algorithm is currently being implemented as a part of an integrated simulation environment, involving the combination of a traffic simulator and a network simulator, which models a complete ITS-G5 protocol stack. Nevertheless, the presented analysis provides valuable insights into the impact of vehicular communication performance on the quality of traffic state estimation in urban environments.

ACKNOWLEDGMENTS

The authors are grateful to the Niedersachsen Institutes of Technology (NTH) for funding the work presented in this paper, which has been conducted within the scope of the project “Planning and Decision Making in Networks of Autonomous Actors in Traffic (PLANETS)”.

REFERENCES


Sixth ACM International Workshop on VehiculAr InterNETworking - VANET '09, 2009, p. 13.


