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Accurate and cost-effective traffic information acquisition using adaptive sampling: Centralized and V2V schemes

Shiau Hong Lim*, Yeow Khiang Chia, Laura Wynter

IBM Research, 10 Marina Boulevard, 018983, Singapore

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ABSTRACT

The new generation of GPS-based tolling systems allow for a much higher degree of road sensing than has been available up to now. We propose an adaptive sampling scheme to collect accurate real-time traffic information from large-scale implementations of on-board GPS-based devices over a road network. The goal of the system is to minimize the transmission costs over all vehicles while satisfying requirements in the accuracy and timeliness of the traffic information obtained. The system is designed to make use of cellular communication as well as leveraging additional technologies such as roadside units equipped with WiFi and vehicle-to-vehicle (V2V) dedicated short-range communications (DSRC). As opposed to fixed sampling schemes, which transmit at regular intervals, the sampling policy we propose is adaptive to the road network and the importance of the links that the vehicle traverses. Since cellular communications are costly, in the basic centralized scheme, the vehicle is not aware of the road conditions on the network. We extend the scheme to handle non-cellular communications via roadside units and vehicle-to-vehicle (V2V) communication. Under a general traffic model, we prove that our scheme always outperforms the baseline scheme in terms of transmission cost while satisfying accuracy and real-time requirements. Our analytical results are further supported via simulations based on actual road networks for both the centralized and V2V settings.

1. Introduction

One of the most effective ways to acquire real-time road traffic information is by using vehicles as probes via mobile phones or dedicated onboard devices (De Fabritiis et al., 2008; Li et al., 2009; Shi and Liu, 2010; Ayala et al., 2010; Vandenberghe et al., 2012; Paulin and Bessler, 2013; Herrera et al., 2010; Seo and Kusakabe, 2015). In particular, dedicated onboard devices are at the heart of the new generation of GPS-based tolling systems (Velaga and Pangbourne, 2014; Qin et al., 2017). While their primary function is to enable GPS-based toll collection, an important secondary function of such devices is to collect pervasive traffic level information on the road network. Indeed, since the vehicles are able to transmit their location and speed, real-time traffic estimations can be obtained, and subsequently used in the estimation of the macroscopic fundamental diagram (Nagle and Gayah, 2014; Du et al., 2016) as well as in applications such as real-time routing and incident detection (Asakura et al., 2017). Furthermore, since GPS-based tolling schemes require placing devices in many, and, in some parts of the world, all of the vehicles traveling on the road network, they allow a far greater degree of road traffic sensing that has been available before.

Most onboard units (OBU) rely on cellular transmission for the bulk of their communications to the central server. In general, cellular transmission are costly, and hence reducing the number of such transmissions is an important criteria in the design of a traffic

* Corresponding author.
E-mail addresses: shonglim@sg.ibm.com (S.H. Lim), ykchia@sg.ibm.com (Y.K. Chia), lwynter@sg.ibm.com (L. Wynter).

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data collection scheme using onboard devices. The other requirement of any traffic data collection scheme is clearly to provide enough traffic data samples on every road link and every time period so that the real-time traffic level estimates are reliably accurate. Thus, the dilemma that the scheme must address is to ensure collection of enough traffic data samples, in both time and space, whilst minimizing the number of samples collected and thus minimizing the number of costly transmissions.

Accuracy of traffic level estimations can be measured as a function of the number of samples obtained and depends on the number of actual vehicles on the road link during each time period. The accuracy of the estimate also depends on the time difference between when the data was collected from the vehicle and when it is used in the traffic level estimate. The accuracy of the estimate can thus be evaluated theoretically and in simulation, under certain assumptions on the traffic generation process.

Cost reduction can be achieved in general via two techniques. The first is random sampling, where only a fraction of the vehicles transmit their traffic data at a given point in time. Clearly, this leads to reduced accuracy when the sample size is low, and higher sampling frequencies may be unnecessarily costly. The second technique is onboard data aggregation: due to typical communications charging schedules which use a minimum charging unit (e.g. 1 kB of data), cost savings can be achieved by aggregating traffic data on the device and aligning the size of each transmission with the minimum charging unit. The latter approach means that some on-vehicle traffic observations (e.g. a vehicle's speed at a particular point in space and in time) will be transmitted late. The tradeoff is then in the timeliness of the data, and hence its relevance to the real-time traffic level, versus the number of transmissions made by each vehicle's onboard device.

We address this problem of designing a system to collect accurate real-time traffic information from large-scale implementations of onboard GPS-based devices over a road network. The goal of the system is to minimize the transmission costs over all vehicles while satisfying requirements in the accuracy and timeliness of the traffic information obtained. The system we design should be effective and accurate using purely cellular communication but should be able to leverage additional communication technologies. In particular, the scheme should be able to take advantage of roadside units equipped with WiFi as well as vehicle-to-vehicle (V2V) dedicated short-range communications (DSRC) where available.

We thus propose an adaptive sampling traffic data collection scheme that incorporates both random sampling and data aggregation with an underlying traffic model so as to provide accuracy guarantees. As opposed to fixed sampling schemes, which transmit at regular intervals, the sampling policy we propose is adaptive to the road network and the importance of the links that the vehicle traverses. We consider first the setting in which vehicles can communicate only with the central server directly. Since cellular communications are costly, in the basic centralized scheme, the vehicle is not aware of the road conditions on the network. Then, we consider the case where vehicles are equipped with DSRC and are able to communicate in a V2V manner, thus transmitting some of their traffic data amongst themselves at no cost as well as to the central server via WiFi-equipped roadside units. We further extend the scheme to handle non-cellular communications via roadside units.

Our scheme makes use of a priority queue concept – i.e., assigning different priority classes to different links in the network. The motivation is that links with different priorities typically have different accuracy and real-time latency requirements depending on the characteristics of the links. By arbitrating across the priority classes we are able to achieve a greater degree of transmission cost reduction while satisfying the accuracy requirements of the most critical road links.

We analyze and compare our proposed scheme with a class of baseline schemes commonly used in mobile traffic data collection, in which transmissions take place on a fixed schedule (Vandenberghe et al., 2012; De Fabritiis et al., 2008; Li et al., 2009; Shi and Liu, 2010; Drira et al., 2016; Fusco et al., 2016; Asakura et al., 2017). Vehicle-to-vehicle communication technologies as part of a vehicular ad hoc network (VANET) have also been discussed for traffic data collection and dissemination in Zhang et al. (2016), Turcanu et al. (2016), Baiocchi et al. (2015), He and Zhang (2016), and Wongdeethai and Siripongwutikorn (2016) but without the adaptive sampling method that we propose here. We assume that non-cellular communications are cost-free relative to cellular communications and do not address issues such as bandwidth limitation in V2V or V2I communications. Our proposed scheme, however, can be used in conjunction with other techniques that address such issues. For instance, recent work by Dai et al. (2016) considers bandwidth allocation schemes between vehicles and roadside units that take into consideration both data freshness and timeliness.

For our analysis and model derivation, we focus on the class of traffic models with Poisson arrival rates. In particular, we assume that the time interval between visits to two links is exponentially distributed. Under a general traffic model, we prove that our scheme always outperforms the baseline scheme in terms of transmission cost while satisfying accuracy and real-time requirements. Our analytical results are supported via simulations based on actual road networks for both the centralized and V2V settings. In particular, while the time interval between simulated link visits does not follow an exponential distribution, we observe experimentally that the Poisson model used for the model derivations is adequate in the sense that the theoretically-optimized control parameters work well.

The remainder of the paper is as follows. We formulate the problem in the next section as well as the traffic generation model used in the evaluation of our scheme. Section 3 defines our proposed adaptive sampling scheme itself and its key properties, along with the baseline scheme to which we shall compare it. Section 4 presents the V2V extension of our proposed scheme. We provide numerical simulation results in Section 5, and Section 6 presents some areas worthy of further study that have arisen from this work.

2. Problem formulation

We assume that the traffic data produced by each vehicle at each time point is collected as a packet. Each packet is associated with a particular road link before transmission. Specifically, the packet contains the vehicle's GPS coordinates and instantaneous speed along with header information required for data transmission. In addition, we assume that a table is maintained in the onboard unit (OBU) such that when the vehicle passes through each road link, according to a given network description, the ID of that road link can be identified on the device itself. This can be done effectively via techniques such as geo-fencing or virtual trip lines (Hoh et al., 2008). The use of such lightweight map-matching on the device itself allows for more effective adaptive sampling since the characteristics of the link can be used in the sampling strategy.

Various kinds of traffic information can be derived from the collected data. One of the more important measures is the real-time average speed on each road link. We assume that, depending on the desired accuracy and timeliness of the real-time traffic information, a minimum sampling rate and a maximum transmission delay can be specified for each link. Our data collection scheme aims at achieving the required sampling rate within the delay tolerance for each link while minimizing the transmission cost.

More precisely, we define the *effective* sampling rate of a particular link as the probability r that a collected packet gets transmitted to the central server *on time*.[1] The on-time rate is defined with respect to a measurement window of length T_w and a delay tolerance α. In particular, a packet that is generated within any period $[t,t+T_w]$ is said to be on-time if it reaches the server at or before $t+T_w+\alpha$, where α is a delay tolerance. Suppose that a packet is generated at time t_0 and transmitted at time t_0+l. It is easy to see that if $l\leqslant\alpha$ then this packet will be on time for all measurement windows that contain t_0. However, if $l>\alpha$, then this packet will be late for some, but not necessarily all measurement windows that contain t_0, assuming that the measurement windows are chosen uniformly at random in time.

As an illustration of translating an accuracy requirement to the effective sampling rate, consider the case of estimating the average speed on a link. Suppose the accuracy requirement is such that we need $Pr(|\hat{S}-\mathbb{E}(S)|<\epsilon)\geqslant 1-\delta$ where $\hat{S}$ is the estimated speed while $\mathbb{E}(S)$ is the true expected speed. Suppose that N vehicles pass through the link in a measurement window and the effective sampling rate is p, then the sample size follows a binomial distribution with parameters N and p. By concentration inequalities (see (Boucheron et al., 2004), for example), one can derive the necessary sample size n such that $\hat{S}$ satisfies the above accuracy requirement. The required sampling rate p is then decided from the binomial distribution. As a concrete example, suppose the range of possible speed is 40 km/h. Suppose the required ϵ is 10 km/h and $\delta=0.1$. By Hoeffding's inequality, a sample size of 26 is sufficient to ensure an error rate of <0.08. Suppose $N=100$, from the binomial distribution, a sampling rate of $p=0.36$ would ensure $n\geqslant 26$ with failure probability <0.02, thereby satisfying the requirement. Note that this is a simple, conservative example. In general, if more information is available regarding the traffic distribution, such as its variance, then one can derive a less conservative sampling rate.

Typically, on a road network, some links have a higher priority in terms of real-time accuracy and data timeliness requirements. This heterogeneity in sampling requirements over the road links can be exploited to achieve considerable savings in transmission cost. We define our sampling scheme to be adaptive to these variations in importance across the road network, and thus achieve the accuracy objectives of the system while significantly reducing its cost.

We thus partition the network links into m priority classes. Each priority class c is then associated with a delay tolerance α_c and an effective sampling rate r_c, for $c=1\ldots m$.

We define formally the problem as follows: Let Θ be a set of data collection schemes. Let $C(\theta)$ be the expected number of transmissions per link visit (i.e. per generated data packet), according to scheme $\theta\in\Theta$. Let $S_c(\theta,\alpha_c)$ be the effective sampling rate of θ on links of class c. Our objective is to minimize C while satisfying the sampling rate and delay constraints. Let $V(\theta)$ be the expected number of link visits per transmission following scheme θ, then maximizing V is equivalent to minimizing C. Thus we aim to solve the following optimization problem,

$$\begin{aligned} &\underset{\theta\in\Theta}{\text{maximize}} && V(\theta) \\ &\text{subject to} && S_c(\theta,\alpha_c)\geqslant r_c,\quad c=1\ldots m. \end{aligned} \tag{1}$$

We assume that the size of the traffic information in each data transmission is relatively small compared to the payload size, which includes transmission header data, as is generally the case. Thus, the cost of the scheme scales with the number of transmissions rather than the size of each transmission.

We focus on the class of traffic models with Poisson arrival rate in our analysis. In particular, we assume that the time interval between two links is exponentially distributed, with mean τ. The priority class of each visited link is independent from the previous links and has a multinomial distribution, where the probability of visiting a link of class c is q_c, for $c=1\ldots m$. It is straightforward to show that the intervals between two links of class c are independent and exponentially distributed, with mean τ/q_c.

3. Proposed adaptive sampling scheme

3.1. Baseline scheme

The most commonly used data collection scheme is to periodically transmit the current state of the vehicle to the central server. This method was proposed for example in Drira et al. (2016). This method can be costly and inefficient, in that the additional cellular transmissions either do not improve the accuracy of the traffic information or are transmitted when the vehicle is traversing links of little to no importance. In terms of our data generation model, we define a baseline scheme where periodically, all data packets generated since the last transmission are transmitted. The only control parameter for this scheme is the fixed transmission period T_b. So, for the baseline scheme $\theta=T_b$.

Recall that our cost function depends on the number of transmissions and not the size of transmissions. To minimize cost, we

[1] We define the effective sampling rate r asymptotically in the following sense. Suppose n packets have been generated and among these, a packet is chosen uniformly at random. Let r_n be the probability that the chosen packet is transmitted on time. Then $r=\lim_{n\to\infty}r_n$.

therefore want to set T_b as large as possible, while satisfying the sampling and delay constraints. Here, the "sampling" is solely due to the fact that some data packets may be transmitted too late and therefore are essentially "dropped".

The effective sampling rate and the expected packets per transmission are given by the following:

Proposition 1. *Let* $\phi_c = \min\{T_w, \max\{0, T_w + \alpha_c - T_b\}\}, c = 1\ldots m$. *Then*

$$S_c(T_b,\alpha_c) = \frac{\phi_c}{T_w} + \frac{(T_w-\phi_c)(T_w-\phi_c+2\alpha_c)}{2T_w T_b}, \quad c = 1\ldots m$$

and

$$V(T_b) = \frac{T_b}{\tau}.$$

Proof. By the independence assumption, each packet class can be treated separately. Fix a measurement window $[0,T_w]$. Suppose a packet is generated at $t \in [0,T_w]$, and is transmitted at time $t+\beta$. Since t is chosen uniformly at random within $[0,T_w]$, the probability that the packet is transmitted on time is given by

$$S_c(T_b,\alpha_c) = \int_0^{T_w} \frac{1}{T_w} Pr(\beta \leqslant T_w + \alpha_c - t)\mathrm{d}t.$$

Noting that

$$Pr(\beta \leqslant T_w + \alpha_c - t) = \begin{cases} 1 & \text{if } t < \phi_c, \\ \frac{T_w + \alpha_c - t}{T_b} & \text{if } \phi_c \leqslant t \leqslant T_w. \end{cases}$$

gives $S_c(T_b,\alpha_c)$. $V(T_b)$ is immediate due to the Poisson rate. □

Proposition 1 assumes that the baseline scheme always transmits after each period, even when there is no data collected within the period. If the scheme is modified such that there is no transmission in such periods, the objective function is

$$V(T_b) = \frac{T_b}{\tau}\left(\frac{1}{1-e^{-\frac{T_b}{\tau}}}\right).$$

In most scenarios of interest the difference is negligible so we ignore this extra factor in the sequel.

Based on Proposition 1, the solution to program (1) is simply the largest T_b that satisfies all constraints:

Corollary 1. *Define the function*

$$T(\alpha,r) = \begin{cases} \frac{T_w + 2\alpha}{2r} & \text{if } \frac{T_w+2\alpha}{T_w+\alpha} \geqslant 2r, \\ T_w(1-r) + \alpha + \sqrt{T_w(1-r)[T_w(1-r)+2\alpha]} & \text{otherwise.} \end{cases} \tag{2}$$

Then the solution to program (1) for the baseline scheme is

$$T_b = \min_{c\in\{1\ldots m\}} T(\alpha_c, r_c).$$

3.2. Proposed adaptive sampling scheme

Our proposed scheme enhances the baseline scheme in two aspects. First, instead of a fixed transmission period, we use a different clock for each type of link. Secondly, a random sampling mechanism is added. We will show that these enhancements result in significant savings in terms of transmission cost.

Thus, a wait time L_c is assigned to each link class $c = 1\ldots m$. Each newly generated packet is added to the queue based on its expiry time, which is the arrival time plus the wait time. In particular, a packet for link type c that arrives at time t_0 is added to the queue with an expiry time $t_0 + L_c$. The top of the queue corresponds to the packet with the earliest expiry time. We define the scheme so that when this time is reached, a probabilistic test is triggered to determine whether or not to transmit the packet.

Specifically, similar to the wait time, a transmission probability p_c is assigned to each link class $c = 1\ldots m$. With probability $1-p_c$, the transmission test fails and the packet is dropped from the queue. Otherwise, the test passes and a transmission is triggered. In this case, *all* packets in the queue are transmitted. The process repeats when the next expiry time is reached. Thus, our proposed sampling scheme is adaptive to the links traversed by each vehicle.

The proposed scheme has $2m$ control parameters for m priority classes, namely, the wait time $L_1\ldots L_m$ and the transmission probability $p_1\ldots p_m$. The optimization problem (1) now has $\theta = (L_1\ldots L_m, p_1\ldots p_m)$. In general for any m the exact form of $V(\theta)$ and $S_c(\theta,\alpha_c)$ is complex and requires a numerical approach where V and S are estimated through simulations. For the case of $m = 2$ however, we can derive closed-form expressions for V and S such that program (1) can be solved efficiently.

3.3. Two-priority-class adaptive sampling scheme

In many practical scenarios, a two-class scheme may be sufficient. In this case, the network is divided into *key* links and other *non-key* links. The key links have a higher required sampling rate and stricter real-time requirement. There can be an optional third class with $L_3 = \infty$ such that packets in this class never trigger a transmission but may be sent along with other packets in order to fully utilize the transmission payload. For this case we derive closed-form expressions for V and S, and describe a relatively efficient way to find a near-optimal solution of (1).

Recall that, as a vehicle travels, the time interval between visits to key or non-key links is exponentially distributed with mean τ. Note that this interval is between two consecutive key or non-key links, as well as between a key and a non-key link, while ignoring any other links that are not designated as either key or non-key. Each visit is a key link with probability q_1, otherwise it is a non-key link, independent of the type of previously visited link. We refer to packets corresponding to key links (resp. non-key links) as key packets (resp. non-key packets).

The four control parameters in the two-class case are:

1. Wait time for key links, $L_1 \geqslant 0$,
2. Wait time for non-key links, $L_2 \geqslant 0$,
3. Transmission probability for key links, $0 \leqslant p_1 \leqslant 1$, and
4. Transmission probability for non-key links, $0 \leqslant p_2 \leqslant 1$.

Typically, key links have higher required sampling rate as well as lower delay tolerance. In this case, the optimal choice for L_1 is usually smaller than L_2. In all our analyses, we assume a restricted parameter space where $L_1 \leqslant L_2$, and define $\Delta = L_2 - L_1 \geqslant 0$. This is without loss of generality since one can always perform a second optimization with the label *key* and *non-key* swapped to obtain a second set of optimal control parameters, and then choose the better one between the two sets of candidate parameters.

To simplify notation, we define the following for the two-class case. Let $q = q_1$, therefore $1-q = q_2$. Let

$$\overline{p} = p_1 q + p_2(1-q) \quad \text{and} \quad \overline{p}' = p_1 q(1-p_2) + p_2(1-q).$$

Our objective is to find the solution to program (1), where $\theta = (L_1, L_2, p_1, p_2)$. To this end, we first derive the expressions for $S_1(\theta,\alpha_1)$, $S_2(\theta,\alpha_2)$ and $V(\theta)$. The following lemma summarizes a few key properties of a single transmission. Since each transmission is independent – the queue is empty after each transmission – the same expectations apply to all transmissions.

Lemma 1. *Assume $m = 2$ and $L_2 \geqslant L_1$. Let i_1 and i_2 be the number of key, and respectively, non-key packets dropped before a transmission is triggered. Let j_1 and j_2 be the number of key (resp. non-key) packets transmitted in a transmission. Let A_1 and A_2 be the probability that a transmitted key (resp. non-key) packet is on-time, over uniform choice of measurement windows. Then*

$$\mathbb{E}(i_1) = \frac{1-p_1}{p_1}\left(1-e^{-\frac{p_1 q \Delta}{\tau}}\right) + \frac{q(1-p_1)}{\overline{p}} e^{-p_1 q \frac{\Delta}{\tau}}, \quad \mathbb{E}(i_2) = \frac{(1-p_2)(1-q)}{\overline{p}} e^{-p_1 q \frac{\Delta}{\tau}},$$

$$\mathbb{E}(j_1) = \frac{qL_1}{\tau} + 1 - \frac{p_2(1-q)}{\overline{p}} e^{-\frac{p_1 q \Delta}{\tau}},$$

$$\mathbb{E}(j_2) = e^{-\frac{p_1 q \Delta}{\tau}} \frac{p_2(1-q)}{\overline{p}} + \frac{1-q}{p_1 q}\left(1-e^{-\frac{p_1 q \Delta}{\tau}}\right) + \frac{L_1(1-q)}{\tau},$$

$$A_1 = \frac{\phi_1}{T_w} + \frac{q(T_w-\phi_1)(T_w-\phi_1+2\alpha_1)}{2T_w \tau \mathbb{E}(j_1)},$$

and

$$A_2 = \frac{\phi_2}{T_w} + \frac{(\phi_3-\phi_2)(1-q)}{T_w \mathbb{E}(j_2)}\left(\frac{L_1}{\tau} + \frac{1}{p_1 q}\right) - \left(e^{\frac{p_1 q}{\tau}\phi_3} - e^{\frac{p_1 q}{\tau}\phi_2}\right) \frac{(1-q)\tau}{T_w (p_1 q)^2 \mathbb{E}(j_2)} e^{-\frac{p_1 q}{\tau}(T_w+\alpha_2-L_1)} + \frac{(1-q)(T_w-\phi_3)(T_w-\phi_3+2\alpha_2)}{2T_w \tau \mathbb{E}(j_2)},$$

where

$$\phi_1 = \min\{T_w, \max\{0, T_w+\alpha_1-L_1\}\},$$

$$\phi_2 = \min\{T_w, \max\{0, T_w+\alpha_2-L_2\}\}, \quad \phi_3 = \min\{T_w, \max\{\phi_2, T_w+\alpha_2-L_1\}\}.$$

The proof is deferred to the appendix. With Lemma 1, we can now derive the expressions involved in the optimization problem (1).

Proposition 2. *Assume $m = 2$ and $L_2 \geqslant L_1$. Let $\theta = (L_1, L_2, p_1, p_2)$ be the parameters for the proposed scheme. Then*

$$S_1(\theta,\alpha_1) = A_1 \frac{\mathbb{E}(j_1)}{\mathbb{E}(i_1)+\mathbb{E}(j_1)}, \quad S_2(\theta,\alpha_2) = A_2 \frac{\mathbb{E}(j_2)}{\mathbb{E}(i_2)+\mathbb{E}(j_2)}$$

and

$$V(\theta) = \mathbb{E}(i_1) + \mathbb{E}(j_1) + \mathbb{E}(i_2) + \mathbb{E}(j_2)$$

where $\mathbb{E}(i_1)$,$\mathbb{E}(i_2)$,$\mathbb{E}(j_1)$,$\mathbb{E}(j_2)$,A_1 *and* A_2 *are as given in* Lemma 1.

Proof. Suppose n transmissions have been completed. Let $i_1^{(k)}$ be the number of key packets dropped in the k-th transmission (i.e. before the k-th but after the $(k-1)$-th). Similarly, let $j_1^{(k)}$ be the number of key packets transmitted in the k-the transmission. Suppose a packet is chosen uniformly at random from among all generated key packets, then the probability that the chosen packet is transmitted (instead of dropped), as $n \to \infty$, is

$$\lim_{n\to\infty} \frac{\sum_{k=1}^{n} j_1^{(k)}}{\sum_{k=1}^{n} i_1^{(k)} + j_1^{(k)}} = \frac{\mathbb{E}(j_1)}{\mathbb{E}(i_1) + \mathbb{E}(j_1)}.$$

Conditioned on a key packet being transmitted, the probability that it is on-time is given by A_1 from Lemma 1. Therefore, we have

$$S_1(\theta,\alpha_1) = A_1 \frac{\mathbb{E}(j_1)}{\mathbb{E}(i_1) + \mathbb{E}(j_1)}.$$

Similar reasoning gives $S_2(\theta,\alpha_2)$.

By definition, $V(\theta)$ is the expected number of packets generated per transmission. A generated packet can either be key or non-key, dropped or transmitted, and therefore $V(\theta) = \mathbb{E}(i_1) + \mathbb{E}(j_1) + \mathbb{E}(i_2) + \mathbb{E}(j_2)$. □

The following result shows that the proposed scheme is never worse than the baseline. This applies to any number of classes.

Proposition 3. *Let* T_b *be the solution to program* (1) *as given by* Corollary 1 *for the baseline scheme and* $V(T_b)$ *be the corresponding objective value. Then there is always a choice of parameters* θ *for the proposed scheme with* $V(\theta) \geqslant V(T_b)$.

Proof. Define the functions

$$L(\alpha,r) = \begin{cases} \frac{T_w + 2\alpha}{2r} - \tau & \text{if } r \leqslant \frac{T_w + 2\alpha}{2(T_w + \alpha + \tau)}, \\ T_w(1-r) + \alpha - \tau + \sqrt{[T_w(1-r)]^2 + 2\alpha T_w(1-r) + \tau^2} & \text{otherwise} \end{cases}$$

and

$$V(\alpha,r) = \frac{L(\alpha,r)}{\tau} + 1.$$

Suppose there is only one class, $m = 1$. From Proposition 2, we can assume $q = 1$ and show that choosing $p_1 = 1$ and $L_1 = L(\alpha_1,r_1)$ will ensure that $S_1(\theta,\alpha_1) \geqslant r_1$. Furthermore, the resulting $V(\theta)$ is given by $V(\alpha_1,r_1)$. With simple calculus it can be shown that $V(\alpha,r) \geqslant V(T_b)$ where $T_b = T(\alpha,r)$ is from (2).

For $m > 1$, choose $p_c = 1$ and

$$L_c = \min_{c' \in \{1 \ldots m\}} L(\alpha_{c'},r_{c'}).$$

for all $c = 1 \ldots m$. The choice of $p_c = 1$ ensures that $S_c(\theta,\alpha_c)$ is a monotonically decreasing function of L_c, which in turn ensures that $S_c(\theta,\alpha_c) \geqslant r_c$ for all $c = 1 \ldots m$. By Proposition 1, the optimal choice for the baseline parameter is $T_b = \min_c T(\alpha_c,r_c)$. Since $V(\alpha_c,r_c) \geqslant V(T(\alpha_c,r_c))$ for all $c = 1 \ldots m$, we have that $V(\theta) \geqslant V(T_b)$. □

Note that the choice of parameters in Proposition 3 is overly conservative since it does not take into consideration the improved performance when there is more than one class of packets. In general, the gain in performance over the baseline scheme is more significant when the parameters are further optimized.

For the 2-class case, with the closed-form expressions for S and V, we propose a simple grid search in the 4-dimensional space Θ. The search space can be greatly reduced by analyzing the feasible regions in program (1). This is described in Section 4.4, where we present results that additionally cover the V2V extension of our proposed scheme.

4. Transmission pooling with V2V

Further savings in transmission cost can be achieved by using other forms of data transmission that avoid cellular communications. When WiFi-equipped roadside units are available, our adaptive sampling scheme adapts readily by triggering a transmission of all of the traffic data in the queue. This can reduce considerably the overall system cost if the roadside units are placed along heavily used links.

A different and complementary approach can be formulated if vehicle-to-vehicle (V2V) communications are available. V2V communication typically leverages the Dedicated Short-Range Communications (DSRC) protocol. We propose to augment the adaptive sampling scheme in this setting to include data pooling. In other words, a vehicle's OBU can be used to aggregate packets not only from its own GPS but also from neighboring OBUs for transmission. Data aggregation is particularly useful when the number of packets generated by the device is less than the payload quantum size for charging. In that case, the OBU can increase the utilization

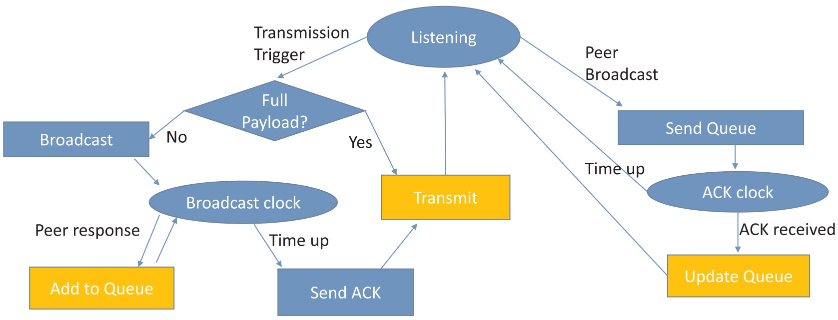

Fig. 1. Overall V2V scheme.

of the transmission payload by pooling packets from nearby OBUs for transmission.

Our V2V scheme sits on top of our priority based sampling scheme and works on a *listener* and *broadcaster* basis. The overall scheme is shown in Fig. 1, and the rest of this section describes the role of the broadcaster and the listener performed by individual onboard units. It is useful to note that DSRC enables V2V communications on the order of 100s of kB over a range of about 100–200 m. Also, note that our approach only employs direct V2V communications and does not require a full multihop vehicular ad hoc network (Zhao and Cao, 2008; Zeadally et al., 2012), which is much more complicated and comes with additional challenges.

4.1. Listener

The listener is the default mode in the V2V scheme. In this mode, the OBU listens periodically for a SEND signal from neighboring vehicles. If a SEND signal is found, the listening OBU will transmit its transmission buffer queue, up to a pre-defined size x bits, to the OBU that transmitted the SEND signal. It then starts a countdown clock with a pre-defined time window and waits for an acknowledgment signal, ACK, from the receiving OBU that its packets have been received. The listener updates its queue by removing all the transmitted packets if an ACK is received. If an ACK is not received in the pre-defined time window, the listening OBU assumes that the transmission has failed and do not delete any packets.

4.2. Broadcaster

The second role of an OBU is that of a broadcaster. This role is activated when the OBU is about to transmit its packets. Before transmission, the OBU first checks its transmission buffer. If there are x bits or more of data in the transmission buffer, the OBU simply sends the packets up to x bits. If the total number of bits in the transmission buffer queue is less than x, the OBU then broadcasts a SEND signal to neighboring OBUs. The broadcasting OBU then waits for a pre-defined time window for other OBUs to transmit their packets to it. If packets are received from another OBU, the broadcasting OBU sends out an ACK to the transmitting OBU and updates its transmission buffer queue. The received packets are inserted into the transmission buffer queue according to transmission as described in the non-V2V setting. This step is carried out for every neighboring OBU that the broadcasting OBU receives its packets from. After the pre-defined time window is reached, the broadcasting OBU proceeds with the transmission.

4.3. Sampling scheme for V2V

Although the same control parameters (i.e. wait time and transmission probability) from the non-V2V case can be used in the V2V setting, the parameters can be further optimized to achieve additional cost savings through V2V sharing. However, assessing the optimal parameters in the V2V setting requires knowledge of the distribution of neighboring vehicles. To this end suppose that a vehicle has established communication to a set of n_0 neighbors. Each vehicle in this set generates data packets independently. According to our scheme, a transmission will transmit all packets in all vehicles of this set. Setting $n_0 = 0$ essentially thus reduces to the non-V2V setting.

The following is the V2V analog to Lemma 1.

Lemma 2. *Assume $m = 2$ and $L_2 \geqslant L_1$. Let i_1 and i_2 be the number of key, and respectively, non-key packets dropped before a transmission is triggered (including transmission triggered by a V2V neighbor). Let j_1 and j_2 be the number of key (resp. non-key) packets transmitted in a transmission. Let A_1 and A_2 be the probability that a transmitted key (resp. non-key) packet is on-time, over uniform choice of measurement windows. Then*

$$\mathbb{E}(i_1) = \frac{1}{n_0+1}\left(\frac{1-p_1}{p_1}\left(1-e^{-\frac{p_1 q (n_0+1)\Delta}{\tau}}\right) + \frac{q(1-p_1)}{\bar{p}} e^{-p_1 q (n_0+1)\frac{\Delta}{\tau}}\right),$$

$$\mathbb{E}(i_2) = \left(\frac{1}{n_0+1}\right)\frac{(1-p_2)(1-q)}{\bar{p}} e^{-p_1 q (n_0+1)\frac{\Delta}{\tau}}, \quad \mathbb{E}(j_1) = \frac{qL_1}{\tau} + \frac{1}{n_0+1}\left(1-\frac{p_2(1-q)}{\bar{p}} e^{-\frac{p_1 q (n_0+1)\Delta}{\tau}}\right),$$

$$\mathbb{E}(j_2) = \frac{L_1(1-q)}{\tau} + \frac{1}{n_0+1}\left(e^{-\frac{p_1 q(n_0+1)\Delta}{\tau}}\frac{p_2(1-q)}{\overline{p}} + \frac{1-q}{p_1 q}\left(1-e^{-\frac{p_1 q(n_0+1)\Delta}{\tau}}\right)\right),$$

$$A_1 = \frac{\phi_1}{T_w} + \frac{q(T_w-\phi_1)(T_w-\phi_1+2\alpha_1)}{2T_w\tau\mathbb{E}(j_1)},$$

and

$$A_2 = \frac{\phi_2}{T_w} + \frac{(\phi_3-\phi_2)(1-q)}{T_w\mathbb{E}(j_2)}\left(\frac{L_1}{\tau} + \frac{1}{p_1 q(n_0+1)}\right) - \left(e^{\frac{p_1 q(n_0+1)}{\tau}\phi_3} - e^{\frac{p_1 q(n_0+1)}{\tau}\phi_2}\right)\frac{(1-q)\tau}{T_w(p_1 q)^2(n_0+1)^2\mathbb{E}(j_2)}e^{-\frac{p_1 q(n_0+1)}{\tau}(T_w+\alpha_2-L_1)}$$
$$+ \frac{(1-q)(T_w-\phi_3)(T_w-\phi_3+2\alpha_2)}{2T_w\tau\mathbb{E}(j_2)},$$

where

$$\phi_1 = \min\{T_w, \max\{0, T_w+\alpha_1-L_1\}\},$$

$$\phi_2 = \min\{T_w, \max\{0, T_w+\alpha_2-L_2\}\}, \quad \phi_3 = \min\{T_w, \max\{\phi_2, T_w+\alpha_2-L_1\}\}.$$

The proof is deferred to the appendix. Analogous to Proposition 2, we can derive the expressions involved in the optimization problem (1) in the V2V case.

Proposition 4. *Assume $m = 2$ and $L_2 \geqslant L_1$. Let $\theta = (L_1, L_2, p_1, p_2)$ be the parameters for the proposed scheme. Then*

$$S_1(\theta, \alpha_1) = A_1\frac{\mathbb{E}(j_1)}{\mathbb{E}(i_1)+\mathbb{E}(j_1)}, \quad S_2(\theta, \alpha_2) = A_2\frac{\mathbb{E}(j_2)}{\mathbb{E}(i_2)+\mathbb{E}(j_2)}$$

and

$$V(\theta) = (n_0+1)(\mathbb{E}(i_1)+\mathbb{E}(j_1)+\mathbb{E}(i_2)+\mathbb{E}(j_2))$$

where $\mathbb{E}(i_1), \mathbb{E}(i_2), \mathbb{E}(j_1), \mathbb{E}(j_2), A_1$ and A_2 are as given in Lemma 2.

4.4. Parameter optimization

For the 2-class case, with the closed-form expressions for S and V, a naive grid search in the 4-dimensional space Θ can still be costly. The following results provide explicit bounds on the feasible regions for L_1 and L_2 in program (1), which can be used to greatly reduce the computational cost. Corollaries 2 and 3 apply to both the V2V and the non-V2V case, depending on the parameter n_0. The corollaries can be derived in a rather straightforward (but tedious) manner based on results in Proposition 4.

Corollary 2. *For $m = 2$, fix p_1 and p_2. Let x_1 and x_2 be the roots of the following quadratic function of x:*

$$x^2 + \left(\frac{2p_1\tau}{\overline{p}(n_0+1)} - 2\alpha_1 - 2T_w(1-r_1)\right)x + \frac{2\tau}{\overline{p}(n_0+1)}(T_w(r_1-p_1)-p_1\alpha_1) + \alpha_1^2.$$

If x_1 and x_2 are imaginary, then the constraint $S_1(\theta, \alpha_1) \geqslant r_1$ is infeasible for this particular pair of p_1 and p_2. If x_1 and x_2 are real with $x_1 \leqslant x_2$, then the constraint $S_1(\theta, \alpha_1) \geqslant r_1$ is only satisfiable for $L_1^l \leqslant L_1 \leqslant L_1^u$, where

$$L_1^l = \begin{cases} x_1 & \text{if } x_1 \geqslant \alpha_1, \\ \max\left\{0, \frac{\tau(r_1-p_1)}{\overline{p}(n_0+1)(1-r_1)}\right\} & \text{otherwise} \end{cases} \quad \text{and} \quad L_1^u = \begin{cases} x_2 & \text{if } x_2 \leqslant T_w+\alpha_1, \\ \frac{T_w+2\alpha_1}{2r_1} - \frac{\tau}{\overline{p}(n_0+1)} & \text{otherwise.} \end{cases}$$

Furthermore, given $L_1 \in [L_1^l, L_1^u]$, the feasible range of L_2 satisfying the constraint $S_1(\theta, \alpha_1) \geqslant r_1$ is $L_1 \leqslant L_2 \leqslant L_2^u$, where L_2^u depends on L_1 as follows,

1. *Case $L_1 \leqslant \alpha_1$*

$$L_2^u = \begin{cases} \infty & \text{if } \frac{L_1}{\tau} + \frac{1}{q(n_0+1)} \geqslant r_1\left(\frac{L_1}{\tau} + \frac{1}{p_1 q(n_0+1)}\right), \\ L_1 + \frac{\tau}{p_1 q(n_0+1)}\log\frac{p_2(1-q)}{\overline{p}\left(1-\frac{L_1 p_1 q(n_0+1)(1-r_1)}{\tau(r_1-p_1)}\right)} & \text{otherwise.} \end{cases}$$

2. *Case $\alpha_1 < L_1 \leqslant T_w + \alpha_1$*

$$L_2^u = \begin{cases} \infty & \text{if } \frac{T_w+\alpha_1-L_1}{T_w}\left(\frac{L_1}{\tau}+\frac{1}{q(n_0+1)}\right)+\frac{L_1^2-\alpha_1^2}{2T_w\tau} \geqslant r_1\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right), \\ L_1+\frac{\tau}{p_1q(n_0+1)}\log\frac{p_2(1-q)}{\bar{p}\left(1-\frac{L_1q(n_0+1)\left(1-r_1-\frac{(L_1-\alpha_1)^2}{2T_wL_1}\right)}{\tau\left(\frac{r_1}{p_1}-1+\frac{L_1-\alpha_1}{T_w}\right)}\right)} & \text{otherwise.} \end{cases}$$

3. *Case* $L_1 > T_w + \alpha_1$

$$L_2^u = \begin{cases} \infty & \text{if } \frac{T_w+2\alpha_1}{2\tau} \geqslant r_1\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right), \\ L_1+\frac{\tau}{p_1q(n_0+1)}\log\frac{p_2(1-q)}{\bar{p}\left(1-p_1q(n_0+1)\left(\frac{T_w+2\alpha_1}{2\tau r_1}-\frac{L_1}{\tau}\right)\right)} & \text{otherwise.} \end{cases}$$

Corollary 3. *For $m = 2$, fix p_1 and p_2. Suppose $L_1 \in [L_1^l, L_1^u]$ where L_1^l and L_1^u are as given in Corollary 2. Then the following are true about the constraint $S_2(\theta,\alpha_2) \geqslant r_2$:*

1. *Case* $L_1 \geqslant T_w + \alpha_2$
   If $\frac{T_w+2\alpha_2}{2\tau} < r_2\left(\frac{L_1}{\tau}+\frac{1}{\bar{p}(n_0+1)}\right)$ *then there is no feasible L_2. Otherwise, the constraint is satisfiable by $L_1 \leqslant L_2 \leqslant L_2^u$ where*

$$L_2^u = \begin{cases} \infty & \text{if } \frac{T_w+2\alpha_2}{2\tau} \geqslant r_2\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right), \\ L_1+\frac{\tau}{p_1q(n_0+1)}\log\frac{p_2(1-q)}{\bar{p}\left(1-p_1q(n_0+1)\left(\frac{T_w+2\alpha_2}{2\tau r_2}-\frac{L_1}{\tau}\right)\right)} & \text{otherwise.} \end{cases}$$

2. *Case* $\alpha_2 \leqslant L_1 < T_w + \alpha_2$
   Let

$$a = \frac{p_1q(n_0+1)(T_w+\alpha_2-L_1)}{\tau} - \frac{\bar{p}}{\bar{p}'} - \frac{p_1q(n_0+1)p_2(1-q)r_2T_w}{\tau\bar{p}'}, \quad \text{and}$$

$$b = \frac{\bar{p}}{\bar{p}'}\left(\frac{(p_1q)^2(n_0+1)^2(T_w(1-r_2)+\alpha_2-L_1)}{\tau}\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right)+\frac{(p_1q)^2(n_0+1)^2(L_1^2-\alpha_2^2)}{2\tau^2}-1\right).$$

   Let x_1 and x_2 be the real solutions to the following equation[2]*:*

$$xe^x = be^a.$$

   The constraint is unsatisfiable if there is no real solution for x. Otherwise, let

$$y_1 = L_1 + \frac{(a-\max\{x_1,x_2\})\tau}{p_1q(n_0+1)}, \quad \text{and} \quad y_2 = \begin{cases} \infty & \text{if } b \geqslant 0, \\ L_1+\frac{(a-\min\{x_1,x_2\})\tau}{p_1q(n_0+1)} & \text{otherwise.} \end{cases}$$

   The constraint is unsatisfiable if $y_1 > T_w + \alpha_2$ or $y_2 < L_1$. Otherwise, the constraint is satisfiable by $\max\{L_1,y_1\} \leqslant L_2 \leqslant L_2^u$ where

$$L_2^u = \begin{cases} y_2 & \text{if } y_2 \leqslant T_w+\alpha_2, \\ \infty & \text{if } y_2 > T_w+\alpha_2 \text{ and } z \geqslant r_2\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right), \\ L_1+\frac{\tau}{p_1q}\log\frac{p_2(1-q)}{\bar{p}\left(1-p_1q\left(\frac{z}{r_2}-\frac{L_1}{\tau}\right)\right)} & \text{otherwise.} \end{cases}$$

   and

$$z = \left(1-\frac{L_1-\alpha_2}{T_w}\right)\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right) - (1-e^{-p_1q(n_0+1)(T_w+\alpha_2-L_1)/\tau})\frac{\tau}{T_w(p_1q)^2(n_0+1)^2} + \frac{L_1^2-\alpha_2^2}{2T_w\tau}.$$

[2] The solution to this equation is the Lambert W function, see Corless et al. (1996).

3. *Case* $L_1 < \alpha_2$

Let

$$a = \frac{p_1q(n_0+1)(\alpha_2-L_1)}{\tau} - \frac{\overline{p}}{\overline{p}'} + \frac{T_w p_1 q(n_0+1)(\overline{p}'-r_2p_2(1-q))}{\tau\overline{p}'}, \quad and$$

$$b = \frac{\overline{p}}{\overline{p}'}\left(\frac{(p_1q)^2(n_0+1)^2T_w(1-r_2)}{\tau}\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right) - e^{-p_1q(n_0+1)(\alpha_2-L_1)/\tau}\right).$$

Let x_1 *and* x_2 *be the real solutions to the following equation:*

$$xe^x = be^a.$$

The constraint is unsatisfiable if there is no real solution for x. Otherwise, let

$$y_1 = L_1 + \frac{(a-\max\{x_1,x_2\})\tau}{p_1q(n_0+1)}, \quad and \quad y_2 = \begin{cases}\infty & if\ b \geqslant 0,\\ L_1 + \frac{(a-\min\{x_1,x_2\})\tau}{p_1q(n_0+1)} & otherwise.\end{cases}$$

The constraint is unsatisfiable if $y_1 > T_w + \alpha_2$ *or* $y_2 < \alpha_2$. *Otherwise, the constraint is satisfiable by* $L_2^l \leqslant L_2 \leqslant L_2^u$ *where*

$$L_2^l = \begin{cases} y_1 & if\ y_1 \geqslant \alpha_2,\\ L_1 & if\ y_1 < \alpha_2\ and\ \frac{L_1}{\tau} + \frac{p_2}{\overline{p}(n_0+1)} \geqslant r_2\left(\frac{L_1}{\tau}+\frac{1}{\overline{p}(n_0+1)}\right),\\ L_1 + \frac{\tau}{p_1q(n_0+1)}\log\frac{\overline{p}'-p_2(1-q)r_2}{\overline{p}(1-r_2)\left(1+\frac{p_1q(n_0+1)L_1}{\tau}\right)} & otherwise.\end{cases}$$

$$L_2^u = \begin{cases} y_2 & if\ y_2 \leqslant T_w + \alpha_2,\\ \infty & if\ y_2 > T_w + \alpha_2\ and\ z \geqslant r_2\left(\frac{L_1}{\tau}+\frac{1}{p_1q(n_0+1)}\right),\\ L_1 + \frac{\tau}{p_1q(n_0+1)}\log\frac{p_2(1-q)}{\overline{p}\left(1-p_1q(n_0+1)\left(\frac{z}{r_2}-\frac{L_1}{\tau}\right)\right)} & otherwise.\end{cases}$$

and

$$z = \frac{L_1}{\tau} + \frac{1}{p_1q(n_0+1)} - \frac{\tau}{T_w(p_1q)^2(n_0+1)^2}\left(e^{-\frac{p_1q(n_0+1)(\alpha 2-L_1)}{\tau}} - e^{-\frac{p_1q(n_0+1)(T_w+\alpha_2-L_1)}{\tau}}\right)$$

With Corollaries 2 and 3, the search for a near-optimal set of parameters can be done very efficiently. Briefly, one defines a grid in the space of $(p_1,p_2) \in [0,1] \times [0,1]$. For each candidate pair (p_1,p_2), Corollary 2 gives the feasible range of L_1. For each feasible L_1, Corollary 2 also gives the feasible range $\mathscr{L}_2^{(1)}$ for L_2 with respect to the constraint S_1, and Corollary 3 gives the feasible range $\mathscr{L}_2^{(2)}$ for L_2 with respect to S_2. The particular (p_1,p_2,L_1) is not feasible if $\mathscr{L}_2^{(1)} \cap \mathscr{L}_2^{(2)}$ is empty, otherwise the optimal L_2 is simply $\max(\mathscr{L}_2^{(1)} \cap \mathscr{L}_2^{(2)})$. We use a resolution of 0.01 for p_1 and p_2, and 1 s for L_1 in our search, and the search typically completes in at most a few seconds on a laptop computer.

5. Simulations

We evaluate the performance of the proposed adaptive sampling scheme on simulated traffic data based on a section of the road network in Singapore. Our map consists of about 9000 links, each with a pre-defined speed limit. Vehicles enter the map via randomly selected points and use the shortest path to reach a randomly selected destination. The speed of each vehicle on a link is bounded within the range $[0.5s,1.1s]$ where s is the speed limit of the particular link. Furthermore, the individual vehicle speed is subject to random but gradual changes throughout its journey.

We randomly designate 1% of the links as key links and 10% non-key links. The selection probability of a particular link is weighted by its frequency of use. All other links are assumed to have no sampling or delay requirements.

In general, it is unlikely that the time interval between link visits follows exactly an exponential distribution. Nevertheless we observe in our simulations that the Poisson model is adequate in the sense that the optimized control parameters work well.

5.1. Transmission cost

We compare the transmission cost of our proposed scheme with the baseline over repeated simulation runs, each lasting 2 h in simulation time. Five measurement windows, each with $T_w = 5$ minutes are selected within the simulation period. The same

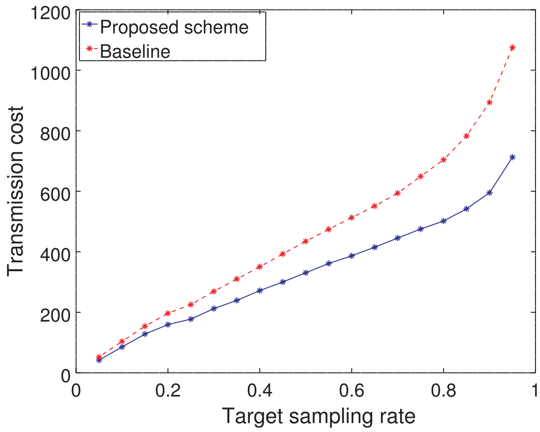

Fig. 2. Transmission cost, $\alpha_1 = 120$, $\alpha_2 = 300$.

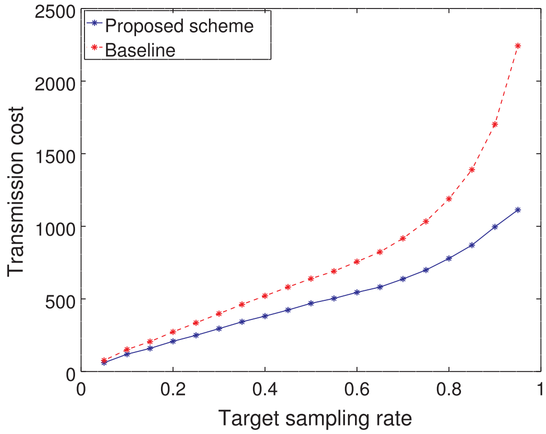

Fig. 3. Transmission cost, $\alpha_1 = 30$, $\alpha_2 = 600$.

measurement windows apply to all repeated trials. We take the average number of transmissions per minute over the simulation period as the transmission cost. We evaluate the performance over a range of sampling requirements. In particular, we first choose a fixed delay tolerance α_1 and α_2, then vary r_1 and r_2 over a wide range. We set $r_1 = r_2$. Figs. 2 and 3 show the results with two different sets of delay tolerance. We observe that in both settings, the proposed scheme outperforms the baseline scheme over the entire range of sampling requirements. The difference is more dramatic when the difference in delay tolerance between key and non-key links is larger, and when the sampling requirements are stronger.

Recall that our default cost function only counts the number of transmissions, regardless of the size of each data transmission. To evaluate the effect of a bounded transmission size, we run the experiments where each transmission is limited to 50 packets, thus penalizing transmissions of large sizes. Fig. 4 shows the results. We observe that the overall performance of both schemes remain similar in this setting, except when the target sampling rate is low. In this regime, both schemes would choose relatively long waiting times, thereby accumulating large number of packets for each transmission, and get penalized for such transmissions.

5.2. Sampling rate and model accuracy

We have seen that the proposed adaptive sampling scheme achieves significant savings in terms of cost. We now examine the performance in terms of the achieved sampling rates. Figs. 5 and 6 show the target sampling rate (i.e. what the parameters are optimized for) and the actual achieved rate, for both key and non-key links.

Note that for key links, the target and actual sampling rates are almost identical. Clearly, the bottleneck constraint is with respect to the (stricter) requirements for the key links. This also shows that although the parameters are optimized with respect to a Poisson model, they nevertheless translate into similar performance in the simulated traffic based on actual road network.

The achieved sampling rate for the non-key links gives some insight on the performance gain afforded by the proposed scheme. In particular, recall that $r_1 = r_2$ so the required sampling rates for both types of links (subject to different latency requirement) are the same. Comparing the achieved sampling rates for non-key links in Figs. 5 and 6, we see that the baseline scheme over-samples the non-key packets due to its inability to adapt to the different requirements between key and non-key links.

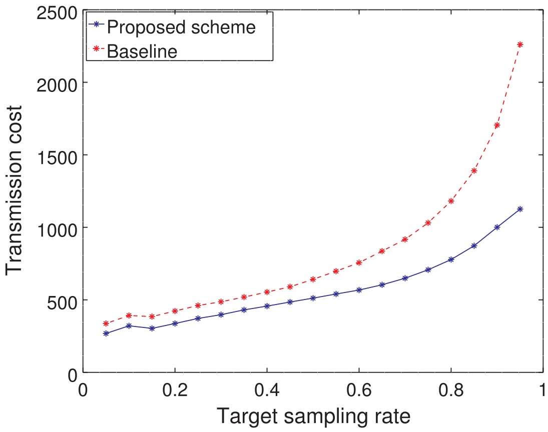

Fig. 4. Modified transmission cost, $\alpha_1 = 30$, $\alpha_2 = 600$.

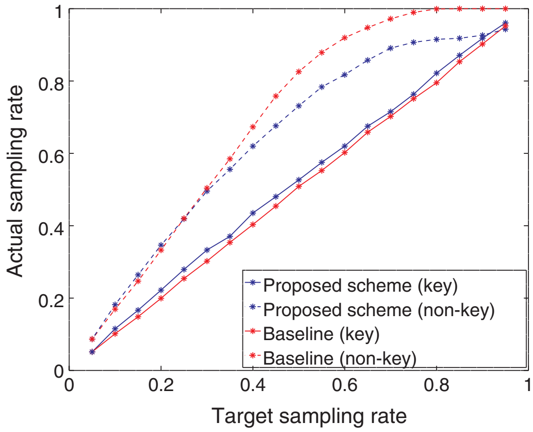

Fig. 5. Sampling rate, $\alpha_1 = 120, \alpha_2 = 300$.

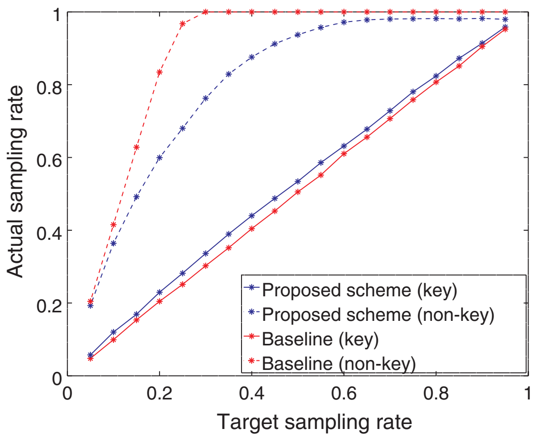

Fig. 6. Sampling, $\alpha_1 = 30, \alpha_2 = 600$.

5.3. Average speed error

The target sampling rate depends on the desired accuracy of the particular piece of traffic information being collected. Here, we examine the errors in estimating the average speed on each link. Figs. 7 and 8 show the errors in estimating average speed in key links. Similarly, Figs. 9 and 10 show the errors on non-key links.

We observe that the error in estimation is a nonlinear function of the sampling rate. For key links, both the baseline and the proposed scheme achieve similar estimation errors. For non-key links, we again observe the effect of over-sampling by the baseline scheme.

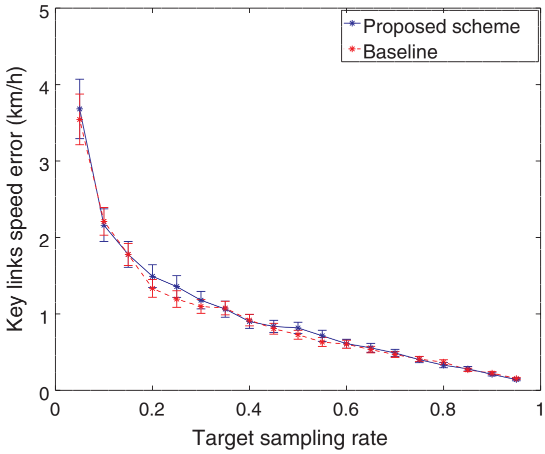

Fig. 7. Speed estimation, $\alpha_1 = 120, \alpha_2 = 300$.

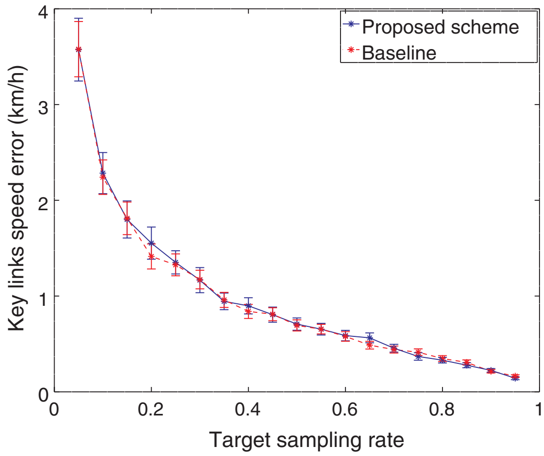

Fig. 8. Speed estimation, $\alpha_1 = 30, \alpha_2 = 600$.

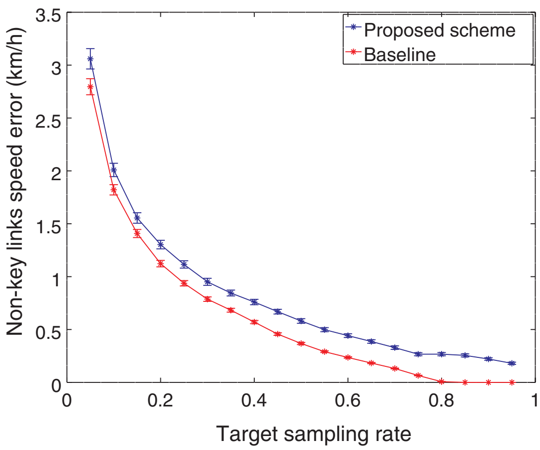

Fig. 9. Speed estimation, $\alpha_1 = 120, \alpha_2 = 300$.

5.4. Numerical simulations with V2V

Next, we evaluate our proposed scheme with the V2V option. Recall that our model requires an estimate of the effective number of neighbors reachable through V2V at any time. Based on simulation runs on our map, the expected number of neighbors is around 10.

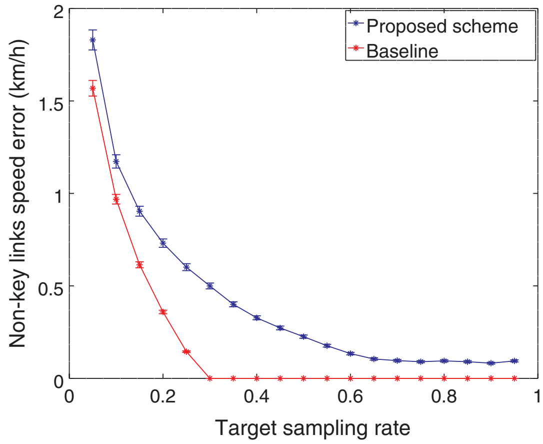

Fig. 10. Speed estimation, $\alpha_1 = 30,\alpha_2 = 600$.

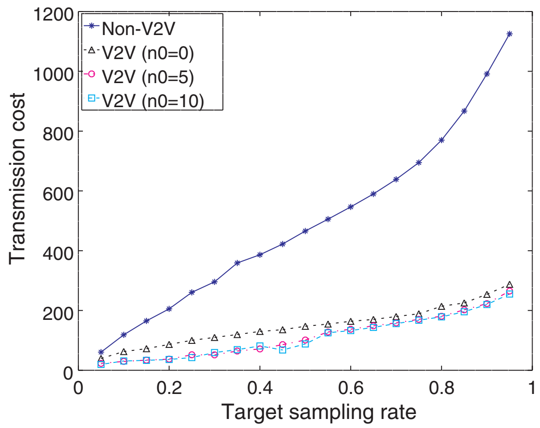

Fig. 11. Transmission cost, $\alpha_1 = 30,\alpha_2 = 600$.

In practice, we recommend a conservative choice of n_0, which should be much smaller than the expectation. We show results where the parameters have been optimized with $n_0 = 0,n_0 = 5$ as well as $n_0 = 10$. The case of $n_0 = 0$ is equivalent to using the optimal parameters for the non-V2V case. We assume that the transmissions involved in V2V communications carry no cost, and the only transmission cost is for the transmission to the central server.

Figs. 11–14 show the results. From Fig. 11, we observe that significant cost savings can be achieved with V2V. It is also obvious that using the non-V2V parameters ($n_0 = 0$) results in significant over-sampling – see Fig. 12. This is especially dramatic when the

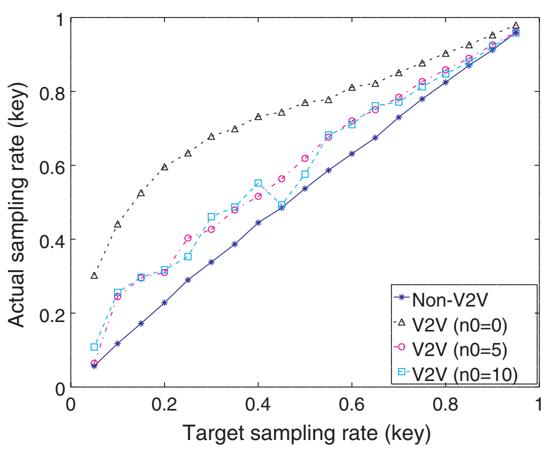

Fig. 12. Sampling rate, $\alpha_1 = 30,\alpha_2 = 600$.

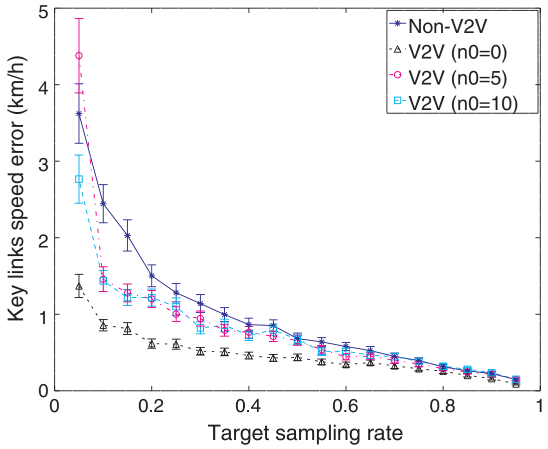

Fig. 13. Speed estimation, $\alpha_1 = 30, \alpha_2 = 600$.

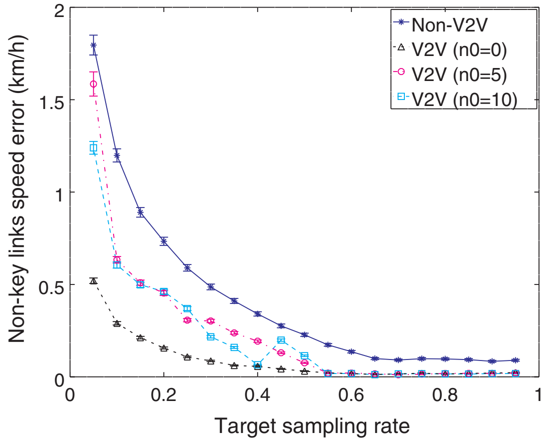

Fig. 14. Speed estimation, $\alpha_1 = 30, \alpha_2 = 600$.

required sampling rate is low, and in this case optimizing the parameters using $n_0 = 5$ reduces the cost significantly. The difference between using $n_0 = 10$ and $n_0 = 5$ is relatively small in terms of both the cost and the achieved sampling rate.

5.5. Error rate with congestion

In this section, we evaluate a scenario of road congestion where the average link speed in the affected links drops significantly. The affected area involves 9 key links where the average normal speed is around 45 km/h, and drops to around 11 km/h during congestion. Figs. 15 and 16 show the absolute and relative mean errors in estimating speed among the affected key links in a 90-min period, where congestion happens within the 30–60-min interval. Note that the relative error increases initially for all methods, and more so for our proposed non-V2V scheme. All schemes have been optimized for a target sampling rate of 0.4 with respect to normal (and Poisson) traffic, for the case of $\alpha_1 = 30$ and $\alpha_2 = 600$. Fig. 17 shows that the proposed Non-V2V scheme slightly under-samples during congestion while the V2V scheme slightly over-samples. We believe that the deviation from the target sampling rate is due to the significant change in traffic flow in this period. However, in practice this impact can be alleviated by optimizing the schemes with respect to a higher, and thus more conservative, sampling rate.

Figs. 19, 18 and 20 show respectively the mean error, actual sampling rate and transmission cost across a wide range of target sampling rates. Because the scheme was not re-optimized for the congested regime, the overall transmission cost is unaffected by the congestion, as expected, since the sampling behavior does experience a significant change, as observed in Figs. 15–17. However, our observation above was that to accommodate unexpected congestion, the scheme's parameters can be made more conservative, with a higher target sampling rate. In this setting, the cost would increase somewhat under the congestion-ready parameters. Analyzing such dynamics is an interesting direction for future work.

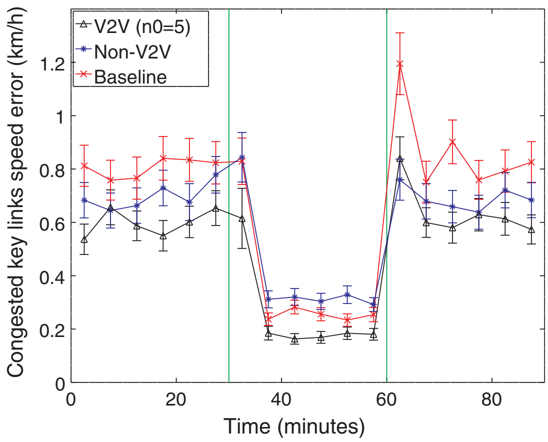

Fig. 15. Speed error (absolute) over time.

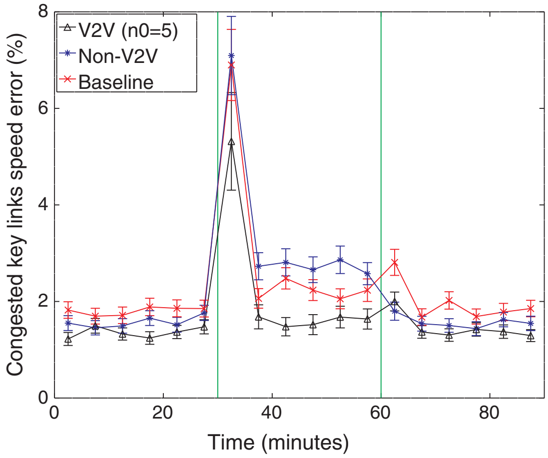

Fig. 16. Speed error (relative) over time.

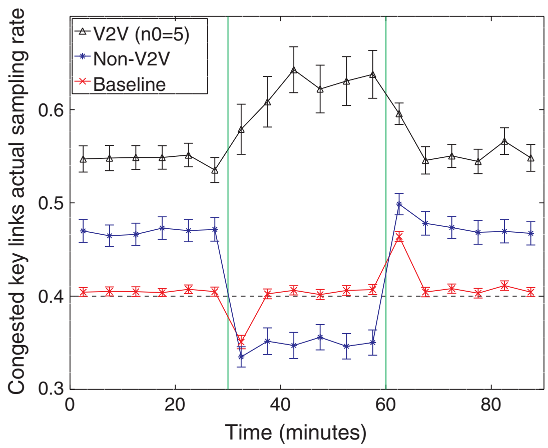

Fig. 17. Effective sampling rate (target = 0.4) over time.

5.6. Cost reduction with WiFi-equipped roadside units

The total system cost can be reduced dramatically when fixed WiFi-equipped roadside units (RSUs) are strategically deployed across the most heavily traveled links on the network. In this case, the tradeoff is between the overall cellular transmission cost and the cost of installing the roadside units. Our proposed scheme can take advantage of such roadside units by transmitting the entire

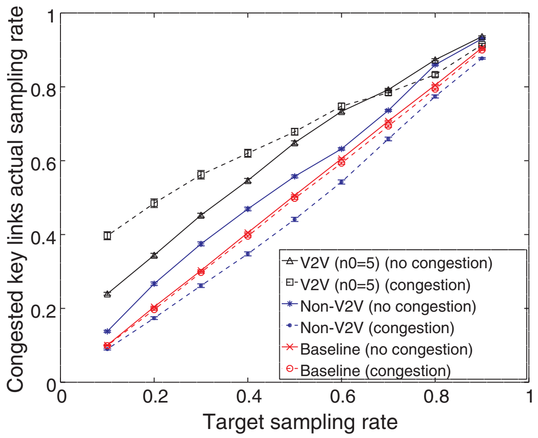

Fig. 18. Effective sampling rate as a function of target sampling rate.

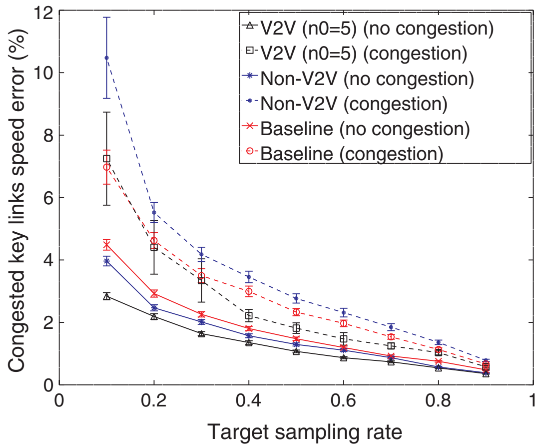

Fig. 19. Speed error (relative) as a function of target sampling rate.

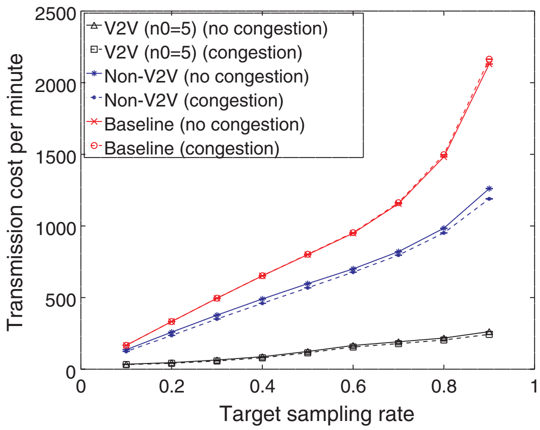

Fig. 20. Transmission cost as a function of target sampling rate.

queue of packets to the roadside unit whenever one is in range. Furthermore, the scheme parameters can also be optimized with respect to the frequency one encounters a roadside unit.

The same analytic approach can be used to optimize the parameters with respect to the presence of RSUs. A simple model is to assume that the duration between consecutive “visits” to fixed roadside units is exponentially distributed with mean τ_0. We omit the full details but illustrate with a simple 1-class example.

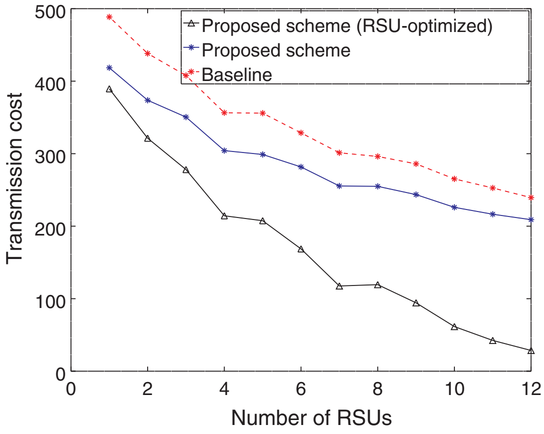

Fig. 21. Transmission cost, $\alpha_1 = 30,\alpha_2 = 600$.

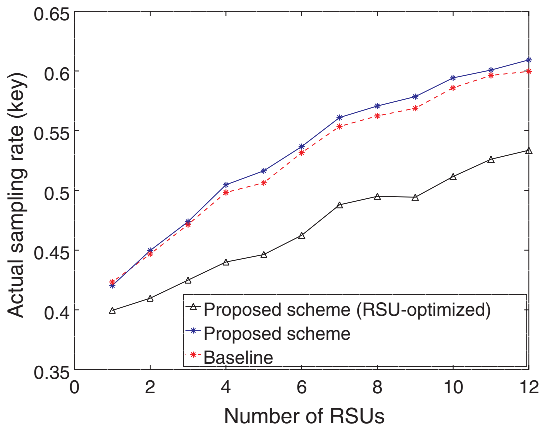

Fig. 22. Sampling rate, $\alpha_1 = 30,\alpha_2 = 600$.

Figs. 21 and 22 show the simulation results when RSUs are strategically placed on the road network. In this case, the links were first sorted by decreasing popularity in terms of their frequency of being traversed by vehicles during the simulation period. The RSUs were added on the map according to this order, subject to a minimum distance separation of 1 km between any two RSUs. For each additional RSU, we estimate a new τ_0 and re-optimize the control parameters.

Fig. 21 shows that the transmission cost goes to zero as more RSUs are added to the network. In this case the all the scheme parameters are optimized with respect to a required effective sampling rate of 0.4. The RSU-optimized scheme adapts to τ_0 while the other two do not consider RSUs in choosing the parameters. From Fig. 21, we see that although all schemes benefit from more RSUs on the network, the RSU-optimized scheme gains the most, while still achieving the required sampling rate. The results also illustrate the fact that the total system cost can be driven to zero as the number of well-placed RSUs increases.

6. Conclusions

We have presented an adaptive sampling scheme for real-time road traffic data collection from pervasive onboard devices across a large-scale road network. The scheme was designed to minimize the number of data transmissions from each vehicle under the assumption that transmissions make use of a cellular network and are hence costly. At the same time the scheme must maintain a minimum level of accuracy of the sampled data, in terms of number of samples obtained. The scheme was designed to leverage other communication technologies when available, such as DSRC between vehicles (V2V) as well as WiFi-equipped roadside units.

The theoretical properties of the scheme were presented and allow us to show that under a general traffic model, our scheme always outperforms the baseline scheme in terms of transmission cost while satisfying accuracy and real-time requirements. The analytical results were confirmed through simulations for both the single vehicle (i.e. vehicle-to-sever) and V2V settings.

This work opens up a number of interesting avenues for further research in the area of adaptive sampling for road traffic data collection. In particular, one may be interested in handling the setting of more than two priority classes. Indeed, when the accuracy requirement is given as a function of the traffic level itself, but should be above e.g. 85%, it may be of use to consider a larger number of priority classes in the scheme. This complexifies the theoretical results presented in this paper, so further assumptions may be required to analyze such cases analytically.

In addition, the adaptive sampling scheme itself may be of use in other domains outside road traffic data collection such as the Internet of Things (IOT). Data collection from mobile or remote devices of many types are ubiquitous and energy consumption related to transmission is of major concern. Hence a similar adaptive sampling scheme can be designed for such devices so that the accuracy of the sampled data can be guaranteed while minimizing the battery consumption associated with data transmission. Examples are mobile medical sensor devices, wearables, and other IOT mobile sensors.

Appendix A. Proof of Lemma 1

Consider a sequence of packets beginning at time $t = 0$ until the first transmission. We now derive the probability of dropping i_1 key packets and i_2 non-key packets before the first transmission, for $i_1 = 0,1,2,\ldots$ and $i_2 = 0,1,2,\ldots$. Denote T as a random variable corresponding to the *arrival time* of the packet triggering the transmission. Denote $K = 1$ the event that the transmission is triggered by a key packet, and $K = 0$ if it is due to a non-key packet. The actual transmission time is therefore $T + L_1$ if in the event of $K = 1$ and $T + L_2$ if $K = 0$.

We are interested in the joint distribution $Pr(i_1,i_2,K,T)$. We split this into 3 cases. Case 1 happens when the first transmission occurs at time $t < L_2$. This can only happen when the transmission is triggered by a key packet since the earliest possible transmission due to a non-key packet is L_2. Let $\Delta = L_2 - L_1$. Case 1 therefore corresponds to $K = 1$ and $T < \Delta$.

In this case, all packets dropped must be key packets and arrive before $t = T$. The arrival time for the $(i_1 + 1)$-th key packet has distribution $\text{Gamma}\left(i_1 + 1, \frac{\tau}{q}\right)$. Averaging over T we therefore have

$$Pr(i_1,i_2 = 0,K = 1,T < \Delta) = (1-p_1)^{i_1} p_1 \int_0^{\Delta} \frac{\left(\frac{qT}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}}}{\frac{\tau}{q} i_1!} \mathrm{d}T = \frac{[(1-p_1)q]^{i_1} p_1 q}{i_1! \tau} e^{-\frac{L_1}{\tau_0}} \int_0^{\Delta} \left(\frac{T}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}} \mathrm{d}T. \tag{A.1}$$

Note that $Pr(i_1,i_2 > 0,K = 1,T < \Delta) = 0$ for all i_1.

Case 2 happens when the first transmission occurs after $t = L_2$ and is due to a key packet, i.e. $K = 1$ and $T \geqslant \Delta$. In this case, all key packets that arrive before $t = T$ are dropped. For non-key packets, only those that arrive before $t = T - \Delta$ will have been tested and dropped. We therefore have that,

$$\begin{aligned} Pr(i_1,i_2,K = 1,T \geqslant \Delta) &= (1-p_1)^{i_1}(1-p_2)^{i_2} p_1 \int_{\Delta}^{\infty} \frac{\left(\frac{qT}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}}}{i_1! \frac{\tau}{q}} \frac{\left(\frac{(1-q)(T-\Delta)}{\tau}\right)^{i_2} e^{-\frac{(1-q)(T-\Delta)}{\tau}}}{i_2!} \mathrm{d}T \\ &= \frac{[(1-p_1)q]^{i_1}[(1-p_2)(1-q)]^{i_2} p_1 q}{i_1! i_2! \tau} e^{(1-q)\frac{\Delta}{\tau}} \int_{\Delta}^{\infty} \left(\frac{T}{\tau}\right)^{i_1} \left(\frac{T-\Delta}{\tau}\right)^{i_2} e^{-\frac{T}{\tau}} \mathrm{d}T. \end{aligned} \tag{A.2}$$

Case 3 happens when the transmission is due to a non-key packet. For this to happen, all non-key packets before $t = T$ must have been dropped. Also, all key packets before $t = T + \Delta$ must have been dropped. We therefore have

$$\begin{aligned} Pr(i_1,i_2,K = 0) &= (1-p_1)^{i_1}(1-p_2)^{i_2} p_2 \int_0^{\infty} \frac{\left(\frac{(1-q)T}{\tau}\right)^{i_2} e^{-\frac{(1-q)T}{\tau}}}{i_2! \frac{\tau}{1-q}} \frac{\left(\frac{q(T+\Delta)}{\tau}\right)^{i_1} e^{-\frac{q(T+\Delta)}{\tau}}}{i_1!} \mathrm{d}T \\ &= \frac{[(1-p_1)q]^{i_1}[(1-p_2)(1-q)]^{i_2} p_2 (1-q)}{i_1! i_2! \tau} e^{-q\frac{\Delta}{\tau}} \int_0^{\infty} \left(\frac{T+\Delta}{\tau}\right)^{i_1} \left(\frac{T}{\tau}\right)^{i_2} e^{-\frac{T}{\tau}} \mathrm{d}T. \end{aligned} \tag{A.3}$$

Adding all three cases, we have that

$$\begin{aligned} Pr(i_1) &= Pr(i_1,i_2 = 0,K = 1,T < \Delta) + \sum_{i_2=0}^{\infty} Pr(i_1,i_2,K = 1,T \geqslant \Delta) + Pr(i_1,i_2,K = 0) \\ &= \frac{[(1-p_1)q]^{i_1} p_1 q}{i_1! \tau} e^{-\frac{L_1}{\tau_0}} \int_0^{\Delta} \left(\frac{T}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}} \mathrm{d}T \\ &\quad + \left(\frac{p_1 q + p_2(1-q)}{\tau}\right) \frac{[(1-p_1)q]^{i_1}}{i_1!} e^{\frac{\Delta}{\tau} p_2 (1-q)} \int_{\Delta}^{\infty} \left(\frac{T}{\tau}\right)^{i_1} e^{-\frac{T}{\tau}(p_2 + q - p_2 q)} \mathrm{d}T. \end{aligned} \tag{A.4}$$

Similarly, we have

$$Pr(i_2) = \mathbb{I}(i_2 = 0)\left(1 - e^{-\frac{p_1 q \Delta}{\tau}}\right) + \left(\frac{p_1 q + p_2(1-q)}{\tau}\right) \frac{[(1-p_2)(1-q)]^{i_2}}{i_2!} e^{-\frac{\Delta}{\tau} p_1 q} \int_0^{\infty} \left(\frac{T}{\tau}\right)^{i_2} e^{-\frac{T}{\tau}(1-q+p_1 q)} \mathrm{d}T. \tag{A.5}$$

With the packet drop probabilities (A.4) and (A.5), we can now derive the expected number of packets dropped before the first transmission as follows:

$$\mathbb{E}(i_1) = \sum_{i_1=0}^{\infty} i_1 Pr(i_1) = \frac{1-p_1}{p_1}\left(1 - e^{-\frac{p_1 q \Delta}{\tau}}\right) + \left(\frac{q(1-p_1)}{p_2(1-q) + p_1 q}\right) e^{-p_1 q \frac{\Delta}{\tau}} \tag{A.6}$$

and similarly

$$\mathbb{E}(i_2) = \frac{(1-p_2)(1-q)}{p_2(1-q) + p_1 q} e^{-p_1 q \frac{\Delta}{\tau}}. \tag{A.7}$$

We now derive the expected number of packets per transmission. Since the number of key packets generated within a time period L_1 is Poisson distributed with mean $\frac{qL_1}{\tau_1}$, the expected number of key packets per transmission is $1 + \frac{qL_1}{\tau_1}$ if the transmission is due to a key packet (i.e. $K = 1$). For $K = 0$ the expected number of key packets is $\frac{qL_1}{\tau_1}$.

First, we have that

$$Pr(K = 0) = \sum_{i_1=0}^{\infty} \sum_{i_2=0}^{\infty} Pr(i_1, i_2, K = 0) = \frac{p_2(1-q)}{p_2(1-q) + p_1 q} e^{-\frac{p_1 q \Delta}{\tau}}. \tag{A.8}$$

Let j_1 be the number of key packets transmitted. Using (A.8) we therefore have

$$\mathbb{E}(j_1) = Pr(K = 1)\left(1 + \frac{qL_1}{\tau}\right) + Pr(K = 0)\frac{qL_1}{\tau} = \frac{qL_1}{\tau} + 1 - \frac{p_2(1-q)}{p_2(1-q) + p_1 q} e^{-\frac{p_1 q \Delta}{\tau}}. \tag{A.9}$$

Similarly, let j_2 be the number of non-key packets transmitted. The expected number of non-key packets transmitted in the event $K = 0$ is $1 + \frac{(1-q)L_2}{\tau}$. In the event $K = 1$, the expectation is $\frac{(1-q)L_2}{\tau}$ if $T \geqslant \Delta$ and $\frac{(1-q)(T+L_1)}{\tau}$ if $T < \Delta$. This is due to the fact that in the latter case, the transmission happens at $T + L_1 < L_2$ and only $\frac{(1-q)(T+L_1)}{\tau}$ non-key packets are generated in this period in expectation.

We then have

$$\begin{aligned}\mathbb{E}(j_2) &= Pr(K = 0)\left(1 + \frac{(1-q)L_2}{\tau}\right) + Pr(K = 1, T \geqslant \Delta)\frac{(1-q)L_2}{\tau} \\ &\quad + \int_0^{\Delta} Pr(K = 1, T)\frac{(1-q)(T+L_1)}{\tau} dT \\ &= e^{-\frac{p_1 q \Delta}{\tau}} \frac{p_2(1-q)}{p_2(1-q) + p_1 q} + \frac{1-q}{p_1 q}\left(1 - e^{-\frac{p_1 q \Delta}{\tau}}\right) + \frac{L_1(1-q)}{\tau}.\end{aligned} \tag{A.10}$$

A key packet that triggers a transmission has a delay of L_1. Suppose this packet arrives at $t = T$, then all key packets that arrive within time $[T, T + L_1]$ will get transmitted. In particular, a key packet that arrives at $t_1 \in [T, T + L_1]$ will have a delay $T + L_1 - t_1$. Similarly, if the transmission is due to a non-key packet that arrives at $t = T$, then a key packet that arrives at $t_1 \in [T + \Delta, T + L_2]$ will get transmitted with delay $T + L_2 - t_1$. For any $0 < \beta < L_1$, due to the Poisson arrival rate, the expected number of key packets that get transmitted with delay at most β is therefore $\frac{q\beta}{\tau}$. Overall, the expected number of key packets with delay β is $\frac{q\beta}{\tau}$. We divide the above by $\mathbb{E}(j_1)$ to obtain the (asymptotic) probability that a transmitted key packet has delay at most β. For a fixed data collection window of size T_w, let $\phi_1 = \min\{T_w, \max\{0, T_w + \alpha_1 - L_1\}\}$. Since the window is chosen uniformly at random, the probability that a transmitted key packet gets accepted is therefore

$$A_1 = \frac{\phi_1}{T_w} + \int_{\phi_1}^{T_w} \left(\frac{1}{T_w}\right) \frac{q(T_w + \alpha_1 - t)}{\tau \mathbb{E}(j_1)} dt = \frac{\phi_1}{T_w} + \frac{q(T_w - \phi_1)(T_w - \phi_1 + 2\alpha_1)}{2T_w \tau \mathbb{E}(j_1)}.$$

Now we look at the delay of transmitted non-key packets. For transmission due to a non-key packet, the expected number of non-key packets with delay at most β for any $0 < \beta < L_2$ is given by $\frac{(1-q)\beta}{\tau}$. For transmission due to a key packet that arrives at $t = T$, the expected number of non-key packets with delay β is $\frac{(1-q)\beta}{\tau}$ for $\beta < T + L_1$ and $\frac{(1-q)(T+L_1)}{\tau}$ for $\beta > T + L_1$. Combining all cases, the expected number of non-key packets with delay at most β is given by

$$\mathbb{E}[j_2; \beta] = \begin{cases} \frac{(1-q)\beta}{\tau} & \text{if } \beta \leqslant L_1, \\ \frac{(1-q)L_1}{\tau} + \frac{1-q}{p_1 q}\left(1 - e^{-\frac{p_1 q(\beta - L_1)}{\tau}}\right) & \text{if } L_1 < \beta < L_2. \end{cases}$$

Let $\phi_2 = \min\{T_w, \max\{0, T_w + \alpha_2 - L_2\}$. Let $\phi_3 = \min\{T_w, \max\{\phi_2, T_w + \alpha_2 - L_1\}\}$. Note that $\phi_2 \leqslant \phi_3 \leqslant T_w$. The probability that a transmitted non-key packet gets accepted is therefore

$$\begin{aligned}A_2 &= \frac{\phi_2}{T_w} + \int_{\phi_2}^{\phi_3} \left(\frac{1}{T_w}\right) \frac{\mathbb{E}[j_2; \beta = T_w + \alpha_2 - t]}{\mathbb{E}(j_2)} dt + \int_{\phi_3}^{T_w} \left(\frac{1}{T_w}\right) \frac{\mathbb{E}[j_2; \beta = T_w + \alpha_2 - t]}{\mathbb{E}(j_2)} dt \\ &= \frac{\phi_2}{T_w} + \frac{(\phi_3 - \phi_2)(1-q)}{T_w \mathbb{E}(j_2)}\left(\frac{L_1}{\tau} + \frac{1}{p_1 q}\right) - \left(e^{\frac{p_1 q}{\tau}\phi_3} - e^{\frac{p_1 q}{\tau}\phi_2}\right) \frac{(1-q)\tau}{T_w (p_1 q)^2 \mathbb{E}(j_2)} e^{-\frac{p_1 q}{\tau}(T_w + \alpha_2 - L_1)} \\ &\quad + \frac{(1-q)(T_w - \phi_3)(T_w - \phi_3 + 2\alpha_2)}{2T_w \tau \mathbb{E}(j_2)}.\end{aligned}$$

Appendix B. Proof of Lemma 2

For the V2V case, we can derive the required expectations following a similar approach as in the non-V2V case. An additional case has to be considered, that is, when a transmission is triggered by a V2V neighbor. From the non-V2V case, the probability that a transmission happens at or after time t (since the last transmission) is

$$Pr(\text{transmit after } t) = \begin{cases} e^{-\frac{p_1 q}{\tau}(t-L_1)} & \text{if } L_1 \leqslant t \leqslant L_2, \\ e^{-\frac{p_1 q}{\tau}(t-L_1)} e^{-\frac{p_2(1-q)}{\tau}(t-L_2)} & \text{if } t > L_2. \end{cases}$$

The probability that none of the neighbors transmit before t is therefore $Pr(\text{transmit after } t)^{n_0}$ since each vehicle acts independently. Denoting the event that a transmission is triggered by any of the neighbors as $K = -1$. In this event, we use small-letter t to denote the transmission time (recall that the capital T denotes arrival time of a transmitting packet). The new joint distribution is given by the following:

$$Pr(i_1, i_2 = 0, K = 1, T < \Delta) = \frac{(1-p_1)^{i_1}}{i_1!}\left(\frac{p_1 q}{\tau}\right)\int_0^{\Delta}\left(\frac{qT}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}(1+n_0 p_1)}\mathrm{d}T$$

$$Pr(i_1, i_2, K = 1, T \geqslant \Delta) = \frac{(1-p_1)^{i_1}}{i_1!}\frac{(1-p_2)^{i_2}}{i_2!}\left(\frac{p_1 q}{\tau}\right)\int_{\Delta}^{\infty}\left(\frac{qT}{\tau}\right)^{i_1} e^{-\frac{qT}{\tau}(1+n_0 p_1)}\left(\frac{(1-q)(T-\Delta)}{\tau}\right)^{i_2} e^{-\frac{(1-q)(T-\Delta)}{\tau}(1+n_0 p_2)}\mathrm{d}T$$

$$Pr(i_1, i_2, K = 0) = \frac{(1-p_1)^{i_1}}{i_1!}\frac{(1-p_2)^{i_2}}{i_2!}\left(\frac{p_2(1-q)}{\tau}\right)\int_0^{\infty}\left(\frac{q(T+\Delta)}{\tau}\right)^{i_1} e^{-\frac{q(T+\Delta)}{\tau}(1+n_0 p_1)}\left(\frac{(1-q)T}{\tau}\right)^{i_2} e^{-\frac{(1-q)T}{\tau}(1+n_0 p_2)}\mathrm{d}T$$

$$Pr(i_1, i_2 = 0, K = -1, L_1 \leqslant t \leqslant L_2) = \frac{(1-p_1)^{i_1}}{i_1!}\left(\frac{n_0 p_1 q}{\tau}\right)\int_{L_1}^{L_2}\left(\frac{q(t-L_1)}{\tau}\right)^{i_1} e^{-\frac{q(t-L_1)}{\tau}(1+n_0 p_1)}\mathrm{d}t$$

$$Pr(i_1, i_2, K = -1, t \geqslant L_2) = \frac{(1-p_1)^{i_1}}{i_1!}\frac{(1-p_2)^{i_2}}{i_2!}\left(\frac{n_0 \overline{p}}{\tau}\right)\int_{L_2}^{\infty}\left(\frac{q(t-L_1)}{\tau}\right)^{i_1} e^{-\frac{q(t-L_1)}{\tau}(1+n_0 p_1)}\left(\frac{(1-q)(t-L_2)}{\tau}\right)^{i_2} e^{-\frac{(1-q)(t-L_2)}{\tau}(1+n_0 p_2)}\mathrm{d}t$$

From here, one can proceed as in the non-V2V case to derive all the remaining terms. We omit the details.

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