Opportunistic WiFi Offloading in a Vehicular Environment: Waiting or Downloading Now?

Ning Wang and Jie Wu
Department of Computer and Information Sciences, Temple University, USA
Email: {ning.wang, jiewu}@temple.edu

***Abstract*—The increasing traffic demand has become a serious concern for cellular networks. To solve the traffic explosion problem in a vehicular network environment, there have been many efforts to offload the traffic from cellular links to Roadside Units (RSUs). Compared with the cost of downloading from cellular link, downloading through RSUs is considered practically free. In most cases, we have to wait for one or several RSUs to download the entire data, which causing huge delays. However, people can always download data from the cellular network. In reality, people are sensitive to the downloading delay but would like to pay little money for downloading the data. As the result, there exists a delay-cost trade-off. In this paper, we unify the downloading cost and downloading delay as the user's satisfaction. The objective of this paper is to maximize the user's satisfaction. A user will be unsatisfied if they are paying too much for data, or if they wait for a long time. We analyze the optimal solution under the condition that the encountering time between vehicles and RSUs follows the exponential and Gaussian distributions. Generally, we propose an adaptive algorithm. A downloading strategy is made based on the historical encountering situation between the vehicle and multiple RSUs. After a period of time, if the real situation is different with the initial prediction, the data downloading strategy will be correspondingly adjusted. Extensive real-trace driven experiment results show that our algorithm achieves a good performance.**

***Index Terms*—Offloading, roadside units, vehicular networks**

I. Introduction

In recent years, the demand for high-speed mobile Internet services has increased dramatically. People expect to connect to the Internet anywhere and anytime, including within their own cars. Content distribution to vehicular users through wireless network access is emerging as a necessity to better facilitate road safety and enhance driving experience. The contents include electronic newspapers, advertisements, road-situation reports, maps with traffic statistics, movie clips, etc. Leading technology companies like Google and Apple all developed the standards for automobile applications [1].

There exist two types of wireless access methods in the vehicular network [2]. Cellular-based access technologies such as 3G/4G and Long Term Evolution, play a vital role in providing reliable and ubiquitous Internet access to vehicles, since the cellular infrastructure is well-planned and widely available. Meanwhile, WiFi-based Access Points (APs) have shown their feasibility in content distribution for vehicles. These APs can be Roadside Units (RSUs) deployed intentionally by network service providers and government departments. They are installed in roadside shops or in buildings and are configured for public access, such as, Google WiFi in Mountain View [3]. These APs are characterized by short-range coverage (hundreds of meters), are relatively cheap, have easy deployment and a high data access rate (a theoretically 6.7 Gbps data rate in 802.11ad) [4].

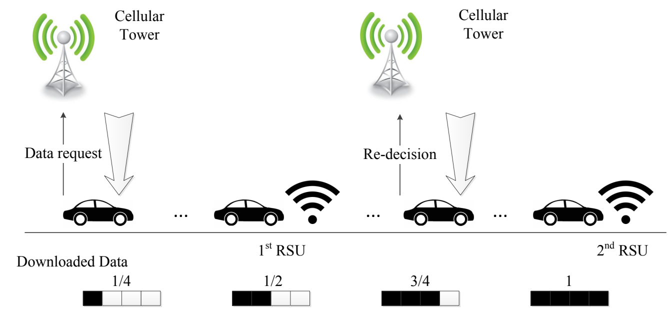


Fig. 1. A network model illustration, where a vehicle can request data from the cellular tower at any time, or waits for opportunistic contact with RSUs.

In this paper, we consider the interfaces scheduling problem in the aforementioned two accessing technologies, i.e., WiFi and cellular network, in the vehicular network. A model is shown in Fig. 1. The vehicle can download data through the cellular network at any time. However, the cost of using this interface is also significant. On the other hand, the vehicle can download the data through opportunistically-encountered RSUs, compared with the cost of using cellular network, it is cost can be regarded as free [5]. Due to the limited contact opportunity with RSUs (tens of seconds), the vehicle might need several encountering opportunities with RSUs to get the entire data. In this case, the user will suffer a long delay, which leads to the data utility decay in reality [6].

From the user's perspective, the user would, ideally, like to download data quickly and inexpensively. There is a trade-off between delay and cost. If we unify the downloading cost and data utility as the user's satisfaction. The user's satisfaction will be low if they pay much for the data, or if they wait for a long time. Therefore, the problem that arises naturally is how to make a decision properly from the two access interfaces, which maximizes the user's satisfaction.

This question is challenging due to the opportunistic encountering with RSUs in the vehicular network. The vehicle might not be able to know the location of the RSUs in the road. Even if we know the location of the RSUs, due to the various traffic conditions, it cannot accurately predict about the encountering time between vehicles and RSUs. Besides, the

978-1-4673-9953-1/16/$31.00 ©2016 IEEE

encountering event between these multiple RSUs is correlated. For example, at the beginning, a vehicle predicted the future encountering events with several RSUs. Then, consider that it meets with a RSU earlier than the initial estimation, due to good traffic conditions, it is highly possible that the vehicle will also meet the next RSU earlier than the initial estimation, and vice versa. Another problem is that the actual situation does not match with our initial estimation. For example, the vehicle did not meet a RSU as expected, or the vehicle does not download the estimated amount of data. The question then becomes, how to make a decision and when should the vehicle adjust its strategy?

We propose an adaptive routing method to solve the user's satisfaction maximization problem. First, when the data request is generated by an application, the vehicle estimates the waiting time from the current location to the next several RSUs, and makes a data downloading decision through these two interfaces. If the vehicle does not encounter with a RSU as expected, the vehicle might re-estimate the encountering time based on the actual situation and do re-decision. The re-decision frequency is highly related to the RSU distribution. An example is shown in Fig. 2, where the vehicle did an initial estimation of the encountering time with the RSUs, and calculated the optimal strategy based on this estimation. The optimal strategy is shown in the gray boxes. However, the real situation might not be the same as the initial estimation. If the vehicle encountered with the RSUs earlier, the vehicle would like to reduce some amount of data, which planned to be retrieved from the cellular network, as shown in the black boxes. If the vehicle did not encounter with the RSUs as expected, the optimal strategy might be to re-download some data from the cellular network, as shown in white boxes.

The contributions of this paper are summarized as follows:

- To our best knowledge, we are the first to propose the opportunistic decision-making problem in the vehicular network with two interfaces, with the data utility decay. The limited contact opportunity is also considered, which makes it more practical than the existing models.
- We analyze the optimal data downloading strategies in the exponential and Gaussian distributions. The theory results provide us a road-map for the solution.
- We propose a novel algorithm in a general situation; the algorithm can dynamically adjust our estimation and adjust the current strategy, if necessary.

The remainder of the paper is organized as follows. The problem statement is introduced in Section II. Then, the theory analysis about the optimal strategies in special distributions is provided in Sections III. The adaptive algorithm is presented in Section IV. The experiment results are shown in Section V. The related works are in Section VI. We conclude the paper in Section VII. Some proofs are provided in the Appendix.

II. Problem Statement

In this section, we first introduce the network model, followed by the problem and the corresponding challenges.

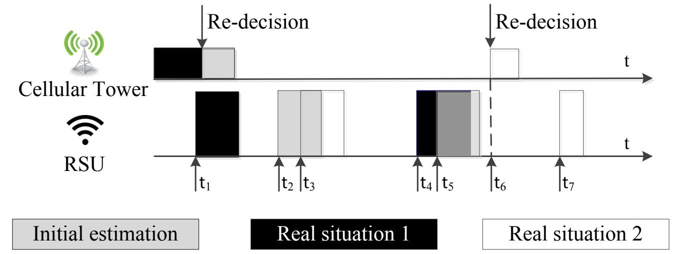


Fig. 2. An illustration of the adaptive data downloading method, where the first timeline represents the time to request data from the cellular network, and the second timeline represents the time to download data through RSUs. Initially, the estimated encountering time with RSUs are t_2 and t_5, respectively. If the vehicle encountered with RSUs in advance, at t_1 and t_4, respectively, the vehicle might download less data from the cellular network. If the vehicle encountered RSUs late, at t_3 and t_7, respectively, the vehicle might decide to download more data from the cellular network at t_6.

A. Network Model

This paper considers a vehicular network with multiple Roadside Units (RSUs), which are connected with the Internet to offer the Internet access for the drive-thru vehicles through WiFi. Due to the variety of the traffic conditions and the RSUs' distribution, we model the encountering between a vehicle (node) and the RSUs as the opportunistic events. The vehicles have two communication interfaces, i.e., WiFi and cellular network. A vehicle can download data from the cellular network at any time for a high price. Compared with the high cost of downloading data from the cellular network, the cost of downloading data from RSUs can be regarded as free [5]. With the wide usage of high-resolution pictures and videos, the entire data can hardly be downloaded instantly, no matter in the cellular network or through RSUs.

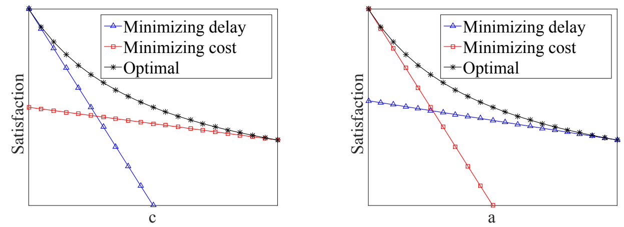
In reality, users are sensitive about the data downloading delay [6]. For example, the old posts on Facebook or Twitter are not so attractive. Here, we model that the vehicle will gain the utility for every bit of data that it downloaded. However, the utility decays along with the time, which reflects the user's time sensitivity for the downloading data. In this paper, we use a linear decay model [7], that is,

$$U_t = U_0 - at, \tag{1}$$

where the initial utility of visual cues is U_0 per bit, then, the utility decays a per second. Note that when $U_0 - at < 0$, we will regard corresponding U_t as 0. The parameter a models the sensitivity of the user, and it has the influence on the offloading decision. If a user is very sensitive to the delay, a is large, the node might prefer to download from the cellular network. Then, if we assume the cost for retrieving data from the cellular network will reduce c utility per bit, we can denote the actual benefit that the vehicle gets from retrieving data through the cellular network as U'_t, $U'_t = U_0 - at - c$. Similarly, the U'_t will not be negative.

B. User's Satisfaction Maximization Problem

The objective of this paper is to find the best download strategy, so that the user's satisfaction, which unifies the



(a) Different data downloading cost (b) Different data utlity decay speed

Fig. 3. User's satisfaction in different scenarios, where the minimizing delay strategy and the minimizing cost strategy mean that the vehicle downloads all the data through the cellular network and RSU, respectively. The optimal solution is got by brute-force computation.

downloading cost and data utility, is maximized. To avoid infinite computing of different strategies, we assume that the vehicle might change its strategy in a discrete manner, per second, as the most adaptive algorithms did. let us denote the data downloaded at the i^{th} seconds as d_i, the moments of using RSU, and the moments of using cellular network as S and S_i', respectively. For example, the vehicle used 1^{st}, 2^{nd}, 5^{th} and 6^{th} seconds to download data from the cellular network, and it encountered with a RSU at the 3^{rd} and 6^{th} second. That is, $S = \{3, 6\}$ and $S' = \{1, 2, 5\}$. If the data size is denoted as M bits, then, the math formulation of the user's satisfaction maximization problem can be written as:

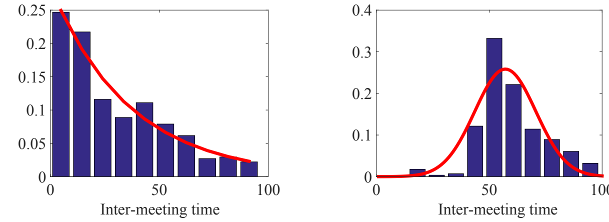
$$\begin{aligned} \max \quad & \sum_{i\in S} U_i d_i + \sum_{j\in S'} U_j' d_j \\ \text{s.t.} \quad & \sum_{i\in S} d_i + \sum_{j\in S'} d_j \geq M, \quad d_i \leq B_r^{max}, \quad d_j \leq B_c^{max} \end{aligned}$$

where B_r^{max} and B_c^{max} is maximum bandwidth in the RSU and the cellular network, respectively.

C. Challenges

The first challenge lies in the trade-off between the utility decay speed and cost. If the utility decays fast, the vehicle would like to download the data right away. That is, the best strategy is to download through the cellular network. On the other hand, if the data utility decays slowly, the vehicle will still get high utility through waiting, so the best strategy is to wait for the RSUs. In any other case, each of above strategies only achieves good performance in certain scenarios, as shown in Fig. 3, where the two simple strategies always downloading data from cellular network or always downloading data from RSUs, can only achieve good performance in certain scenario.

The second challenge is caused by the dynamic situation changing. The vehicle's estimation about the future also changes along with the dynamic situation. If the vehicle did not encounter a RSU as estimated, or it estimates that it will encounter a RSU later than the initial estimation, should the vehicle adjust its downloading strategy, and how to adjust its strategy is a challenging problem. Besides, how to estimate the future event, and when to adjust the future estimation is non-trivial. For example, the vehicle initially estimated that it



(a) No.3204 bus (b) No.5676 bus

Fig. 4. Inter-encountering distribution between a vehicle and RSUs in Diesel.

would encounter with two RSUs at the 5^{th} second and 10^{th} second, respectively. If it actually encountered with the first RSU at the 4^{th} second, will it meet the second RSU at the 9^{th} or 10^{th} second?

Another challenge is how to assign the weight to the prediction. If the vehicle just uses the expected encountering time and the corresponding duration with the RSUs to calculate the downloading strategy as in a static environment, there exists the risk, that the vehicle actually encountered the RSUs later, the data utility will decrease. However, if the vehicle downloads much data through cellular network at the beginning, it might not fully use the free opportunistic data downloading through roadside WiFi.

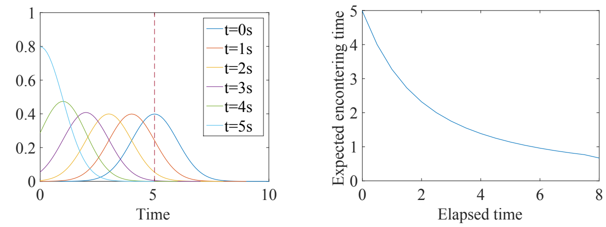
III. Optimal Strategy in Special Distributions

In this section, we analyze the optimal download strategies under the assumption that the encountering time between the vehicle and RSUs follows exponential and Gaussian distributions. The reason is that the real situation is always one or a mixture of these two. Examples in the literature are [8, 9]. We also verified the real situation in Diesel Bus Dataset [10]. In Fig. 4, we show the encountering time distributions between No. 3204 and No. 5676 bus and RSUs in Diesel Dataset as an example. For the analysis, we start with the simple case, that the Bandwidth of the RSUs is unlimited. Then, we move to a general case, that the bandwidth of the RSUs is limited.

A. Offloading through a Single Roadside Unit

In the single RSU model, this RSU can provide the remaining data. The data downloading procedure will end, when the vehicle meets a RSU. Let us denote $f(t)$ as the probability density function (PDF) of the encountering between vehicle and the RSU at time t, and $F(t)$ as the cumulative distribution function (CDF) of the encountering between vehicle and the RSU in time t, respectively. Then, the user's expected satisfaction in T is written into the following format:

$$\begin{aligned} &\sum_{t=0}^{T} \Big(\sum_{i=0}^{t} U_i' d_i + U_{t+1} d_{t+1} \Big) (1 - F(t)) f(t+1) = \\ &\sum_{t=0}^{T} \Big(\sum_{i=0}^{t} (U_0 - c - ai) d_i + (U_0 - a(t+1)) d_{t+1} \Big) (1 - F(t)) f(t+1), \end{aligned} \tag{2}$$



(a) Probability density function (b) Expected enountering time

Fig. 5. Probability change along with the time in the Gaussian distribution. Fig. 5(a) is the PDF in different time. For example, $t = 1s, 2s, 3s, 4s$ and $5s$ means that the PDF after $1s, 2s, 3s, 4s$, 5s, respectively.

where $(1 - F(t))f(t+1)$ represents the probability that the vehicle does not meet a RSU at the first t seconds, but meets a RSU at the $t+1$ second. $\sum_{i=0}^{t} U_i' d_i + U_{t+1} d_{i+1}$ is a general function to represent the user's satisfaction for any downloading strategy. Then, our main concern is to decide the $\{d_i, \ldots, d_T\}$. In the following, we will analyze the downloading strategies in two special distributions.

1) Exponential distribution of the encountering rate between the vehicle and RSUs: The application scenario is that the vehicle is leaving the center city, so that the longer it waits, the smaller chance that it will meet a RSU. Assume that the encountering rate between vehicle and RSUs is λ. Then, the Eq. 2 can be written into the following equation:

$$\sum_{t=0}^{T}\Big(\sum_{i=0}^{t}(U_0 - c - ai)d_i + (U_0 - a(t+1))d_{i+1}\Big)e^{-\lambda t} \cdot \lambda e^{-\lambda(t+1)}. \tag{3}$$

Theorem 1. *For exponential distribution of the encountering time between the vehicle and RSUs, the vehicle only needs to do the decision once: download from the cellular network right now, or never. The criterion of choosing the cellular network right now is* $\frac{a}{2\lambda} > c$.

The proof is appended at the end of the paper. The insight is that the exponential distribution has the memoryless property, so that we cannot get better prediction with the increasing of time. For example, if the expected encountering time is 5s, after 1s, the expected encountering time is still 5s. However, the longer you wait, the less utility of data it will be. Therefore, the vehicle should decide to use the cellular network right away, or never. As for the interface selection, if the cost of the cellular network is large, it is more beneficial to wait for a RSU. If the data utility decay or the inter-encountering time is small, the vehicle prefers to wait for a RSU.

2) Gaussian distribution of the encountering rate between the vehicle and RSUs: It can reflect the situation in the urban area. Usually, the vehicle will take an average time to encounter with a RSU. Sometimes, however, the vehicle will meet a RSU in a really short or long time. In Gaussian distribution, along with time, our estimation about the future will become more and more accurate. The Fig. 5 shows a vehicle's estimation about the future in the Gaussian distribution. The expected encountering time is initially 5s; As time elapses, the prediction uncertainty decreases, as shown in Fig. 5(a). When $t = 5$s, a large amount of probability density (higher than $t = 0$s) is centered at the near future, and the expected encountering time with a RSU from now decreases, as shown in the Fig. 5(b). Note that the estimation changing does not have a linear relationship with the time.

Due to the difficulty of doing the operation for the CDF of Gaussian distribution, we use a Gaussian-like distribution made by a polynomial function to approximate it. The PDF and the CDF of this distribution are shown in the following:

$$\begin{cases} f(t) = \frac{t^{\beta}}{w} & (0 < t < T^e) \\ f(t) = \frac{(t - 2T^e)^{\beta}}{w} & (T^e < t < 2T^e), \end{cases} \tag{4}$$

where the vehicle has the probability of encountering the RSU from $t \in [0, 2T^e]$, and β is a constant, which controls the variance of the probability distribution, the same as variance, σ, in the Gaussian distribution, and w is the normalization factor. It is easy to know the expected encountering time is T^e. Then, we can calculate the CDF of $f(t)$:

$$\begin{cases} F(t) = \frac{t^{\beta+1}}{(\beta+1)w} & (0 < t < T^e) \\ F(t) = 1 - \frac{(2T^e - t)^{\beta+1}}{(\beta+1)w} & (T^e < t < 2T^e). \end{cases} \tag{5}$$

If we substitute Eqs. 4 and 5 into Eq. 2, we will get the following result: if we choose to download data from the cellular network right now, the user's satisfaction is

$$\frac{2T^e(U_0 - c)}{w^2}\Big(\sum_{t=1}^{T^e}(1 - \frac{t^{\beta+1}}{\beta+1})t^{\beta} + \sum_{t=T^e}^{2T^e}\frac{(2T^e - t)^{\beta+1}}{\beta+1}(2T^e - t)^{\beta}\Big). \tag{6}$$

The expected satisfaction after one second to meet a RSU is

$$\begin{aligned} &\frac{2T^e(U_0 - c - a)}{w^2}\Big(\sum_{t=1}^{T^e}(1 - \frac{t^{\beta+1}}{\beta+1})t^{\beta} \\ &+ \sum_{t=T^e}^{2T^e}\frac{(2T^e - t)^{\beta+1}}{\beta+1}(2T^e - t)^{\beta} + \frac{c}{w^2}(1 - \frac{1}{\beta+1})\Big). \end{aligned} \tag{7}$$

By comparing the Eqs. 6 and 7, we can get the theorem 2:

Theorem 2. *For Gaussian distribution of the encountering time between the vehicle and RSUs, the criterion for choosing the cellular network right now is* $\frac{(T^e)^{\beta+1}a}{\beta} > c$.

The proof is appended at the end of the paper. The reason that we compare the benefit of the first two seconds is that we are concerned about whether the vehicle will download data from the cellular network now. It is a conservative estimation. The insight behind the result is that if the cellular network is expensive or the utility decays slowly, the vehicle prefers to wait. If the predicted encountering time, T^e, appears late, the vehicle prefers to download from the cellular network. When β is large, the majority of probabilities are centered in the T^e, thus, waiting becomes less beneficial. For example, we estimate that the vehicle will encounter with a RSU after 5 minutes. If the uncertainty is low, the vehicle can almost encounter at the 5^{th} minute, and our prediction about the future is very certain. However, if the uncertainty is high, the vehicle might have a high probability of encountering the vehicle at the 6^{th} minute, which will cause extra utility loss.

B. Offloading through Multiple Roadside Units

Due to the limited contact opportunity between the vehicle and RSUs, a practical model is that the vehicle will finish downloading the data after encountering with several RSUs.

In this scenario, the encountering situation in one RSU has an influence on the future event. For example, if the inter-encountering time between RSUs are independent, and the average inter-encountering time is 5 minutes, a vehicle estimated that it would meet the 2^{th} RSU at 10^{th} minute. However, the vehicle has the possibility to meet the 1^{th} RSU at the 4^{th} minute. Then, the estimated encountering time with the second RSU should be the 9^{th} minute, rather than at the 10^{th} minute. In general, let us assume that the inter-encountering time between two adjacent RSUs is independent, the inter-encountering time PDF of the k^{th} RSUs from the current location is Eq. 8.

$$f(t_1, t_2, \ldots, t_k) = \frac{1}{q} \cdot f_1(t) * f_2(t) \cdots * f_k(t), \tag{8}$$

where $f_i(t)$ is the independent inter-encountering PDF from the $(i-1)^{th}$ RSU to the i^{th} RSU and $*$ denotes the convolution. The $f(t_1, t_2, \ldots, t_k)$ is the joint encountering time distribution between the vehicle and the k^{th} RSU.

1) Identical exponential inter-encountering time distribution of the encountering rate between two RSUs: It means that the probability of arriving at the next RSU from the current RSU in t second is $f_(t) = \lambda e^{-\lambda t}$, where λ is the rate.

Theorem 3. *If the inter-encountering time distribution of the encountering rate between two RSUs follows the identical exponential distribution, and the encountering rate is λ, the encountering distribution of kth RSU is $f(t_1, t_2, \ldots, t_k) \approx \frac{1}{\sigma_k\sqrt{2\pi}} e^{\frac{t-\mu_k}{2\sigma_k^2}}$, where $\mu_k = \frac{k}{\lambda}$ and $\sigma_k = \frac{\sqrt{k}}{\lambda^2}$.*

The proof is appended at the end of the paper. The insight of this theorem is that the expected encountering time of k^{th} RSU remains the same. However, the variance of the estimation increases in a $\sqrt{k}$ matter. That is, the estimation accuracy decreases along with the distance increases.

2) Identical Gaussian inter-encountering time distribution of the encountering rate between two RSUs: It means that probability of arriving the next RSU from the current RSU in t second follows the Gaussian distribution. We use identically Gaussian distribution to estimate the inter-encountering time probability between two RSUs, that is, $f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\bar{t})^2}{2\sigma^2}}$. where $\bar{t}$ is the expected time to encounter with the next RSU. Then, we can get the following theorem.

Theorem 4. *If the inter-encountering time distribution of the encountering rate between two RSUs follows the identical Gaussian distribution, the encountering distribution of k^{th} RSU is $f(t_1, t_2, \ldots, t_k) = \frac{1}{\sigma'_k\sqrt{2\pi}} e^{-\frac{(t-t'_k)^2}{2\sigma'^2_k}}$ where $t'_k = k\bar{t}$ and $\sigma'_k = \sqrt{k}\sigma$.*

Algorithm 1 Dynamic decision making

Input: Utility decay function $U(t)$, encountering interval distribution estimation, the bandwidth of cellular network and RSUs B_c and B_r, respectively.

Output: The downloading strategy of the vehicle.

1: Estimate the requested data size and the encountering time with first RSU based on the APP type and the RSUs' encountering history. Do decision based on Eq. 11.
2: Get the data size information after the vehicle encounters with the first RSU. Adjust the decision, if necessary.
3: Do re-decision after encountering with a RSU, or the time exceeds the predicted decision interval.

The proof is appended at the end of the paper. The insight behind this theorem is that the opportunistic encountering will not change the expected encountering time, but increases the uncertainty about estimation of encountering with further RSUs. If the encountering distribution is Gaussian distribution, the uncertainty about the next k RSUs increases $\sqrt{k}$ time.

The above two theorems show that the expected encountering time with RSUs will not change, but the vehicle's estimation about the future event will become more uncertain. Therefore making a distant prediction is unreliable.

IV. The Solution in General Scenarios

Based on the theoretical analysis from the Section III, we figure out the two important factors for estimating the opportunistic encountering with the RSUs, the expectation encountering time, and the uncertainty of the expectation. Therefore, our adaptive algorithm considers these two factors.

1) Decision making: Assume the vehicle expects to meet the n RSUs after $\{T_1, T_2, \ldots, T_n\}$, and the uncertainty of estimation is $\{\sigma_1, \sigma_2, \ldots, \sigma_n\}$, respectively. During each contact opportunity, the vehicle can download $\bar{m}$ bits on average through RSU, and the entire data can be download in n times without using cellular network. If the vehicle decides to use the cellular network, it should download data as soon as possible. Then, we can get the lowest cost to download the data from the cellular network. The user's satisfaction by this strategy is

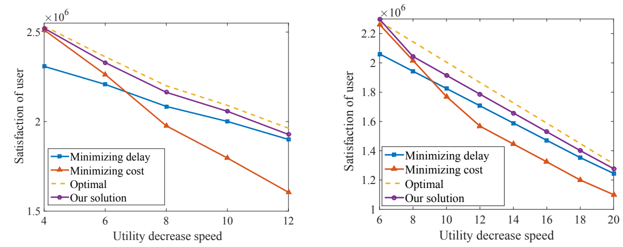
$$\bar{m}n(U_t - \frac{\bar{m}n}{2B_c}a - c). \tag{9}$$

Additionally, the overall utility by waiting for the RSUs is

$$\sum_{i=1}^{n} \bar{m}(U_t - a\sum_{k=1}^{i}(T_k + \sigma_k)). \tag{10}$$

It is a conservative estimation, since we consider the worst case. Though we might not fully use the offloading opportunity, the user's experience will be better. Based on Eqs. 9

Fig. 6. Meeting positions of a bus with RSUs in Diesel data trace, where the red marker represents the contact records between a vehicle and RSUs



(a) Exponential distribution (b) Gaussian distribution

Fig. 7. Utility decay speed

and 10. if downloading from the cellular network is better, the following in-equation will hold,

$$(\sum_{i=1}^{n}\sum_{k=1}^{i}(T_k+\sigma_k)-\frac{\bar{m}n^2}{2B_c})a > nc. \qquad (11)$$

The observation from the Eq. 11 is that the best strategy is to use the cellular network to download data, when the WiFi speed is slow or the average waiting time is long, i.e., n is large. Otherwise, it is more beneficial to wait. Also, the uncertainty degree has an influence on the decision. As for the amount of data that the vehicle should download through the cellular network, the vehicle should continue downloading until the Eq. 11 is not held. When $T_1 = \cdots = T_n = T$, and $\sigma_k = \sqrt{k}\sigma$, Eq. 11 can be simplified into

$$(T-\frac{\bar{m}}{B_c})na > 2c - aT - \frac{4}{5}\sqrt{n^3}\sigma. \qquad (12)$$

2) Re-decision: Due to the fact that our estimation will improve with time, slight adjustments to our decision will be made in a certain frequency. This frequency is related to the distribution about the encountering time with RSUs. Based on the history encountering summary, the vehicle calculates the encountering time distribution to estimate the frequency.

3) RSUs encountering prediction: Here, we try to estimate the future encountering time from the current time by using the historical records. We use the exponentially weighted moving average (EWMA) method; that is, we give the different weight on the past encountering interval. The idea is that the most recent event has a bigger influence on future event prediction,

$$T_{k+1} = \alpha T_k + (1-\alpha)T_{k-1}, \qquad (13)$$

where the window size and α are empirical values.

4) Algorithms: The vehicle estimates the data size based on the application type, and decides whether to download some data through the cellular network or not. Then, when the vehicle encounters the first RSU, it will get the actual size of this data. Now, the vehicle will adjust its decision based on the current situation, if necessary. Later, after a certain period, it will do re-decision to adjust the situation at that time. The decision frequency is also adjusted along with the RSUs' encountering frequency. By using the historical records, we can get the distribution of encountering interval, so that we can adjust our decision frequency adaptively. Basically, if the encountering interval increases, we can reduce the decision frequency. Otherwise, we should do decision more frequently.

V. Performance Evaluations

In this section, we compare several algorithms mentioned in this paper by extensive experiments. We first introduce the experiment settings and their parameters. Then, we will discuss the performance evaluation results.

A. Trace Introduction

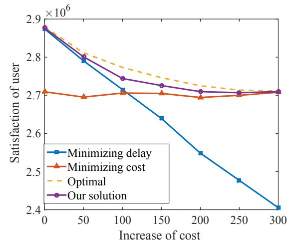
1) Synthetic trace: We generate random encountering events between RSUs and vehicles, where the encountering distribution follows the exponential distributions or the Gaussian distribution. The expected contact interval, and the bandwidth between them are all the same.

2) Real trace: Here, we use DieselNet [10] traces to do evaluations. DieselNet traces were compiled during Fall 2007 from buses running routes serviced by Umass Transit. Umass Transit's 40 buses were equipped with DieselNet equipment. Each bus scans for a connection with RSUs on the road, and when found, connects to the RSUs. As you can see from Fig. 6, the 47 RSUs generate 301 contact positions. The encountering position between the buses and RSUs is opportunistic.

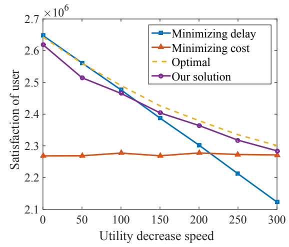
In the experiment, we assume data utility decays in a linear manner. The bandwidth of WiFi and cellular network for one application in the movement situation, referring from the [2], is set as 100 kbps and 20 kbps, respectively. The average data size is assigned as 6M, which is the size of multimedia newspaper or a piece of song [11].

B. Algorithm Comparison

Here, we use four algorithms to do performance comparisons. 1) The minimal delay algorithm: the vehicle keeps downloading data from the cellular network, and uses the opportunistic encountered RSUs to download at the same time. 2) The minimal cost algorithm: the vehicle always waits for RSUs to download data unless the data utility is reduced to zero. 3) The optimal solution: we use the encountering records in the vehicles to do post-analysis. That is, we know the actual encountering time with the RSUs. Then, we use the brute-force method to get the best solution. 4)The proposed algorithm: the vehicle adaptively selects the two interfaces, according to the current situation, to download data.

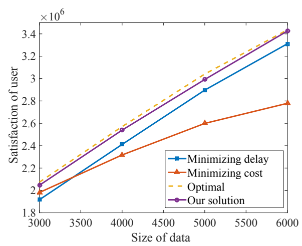


(a) Exponential distribution

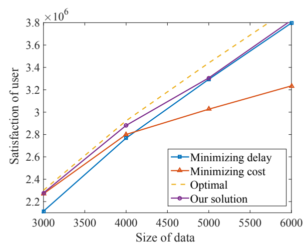


(b) Gaussian distribution

Fig. 8. Cost for cellular network



(a) Exponential distribution



(b) Gaussian distribution

Fig. 9. Size of data

C. Experiment Results

In synthetic data traces, the initial data utility is $1,000$ units. The average encountering interval is 20s. Figs. 7, 8, and 9 depict results from exponential distribution and Gaussian distribution, respectively. The minimizing delay algorithm performs well, when the utility decay of data is large or the cost of the cellular network is small. For the minimizing cost algorithm, it achieves a good performance, when the utility decay of data is small or the cost of a cellular network is large. Our proposed algorithm always achieves a relatively good performance in different scenarios. We also compare our solution with the optimal solution. The results show that our proposed solution is close to the optimal solution. As for the cost variation, when cost is small, our proposed algorithm is close to the minimizing delay algorithm. When the cost is large, our algorithm is close to the minimizing cost algorithm. In the middle, our algorithm can adjust the vehicle's solution to achieve a larger user's satisfaction. The results indicate that the proposed algorithm achieves more than 90% than the optimal solution. The proposed algorithm achieves 15% more utility than those two simple strategies.

As for the influence of the uncertainty, we adjust the variance to be 0s, 8s, and 15s in the Gaussian distribution, respectively. As shown in Fig. 10, when the variance is 0, our proposed algorithm achieves the same performance as the optimal one. Then, when the variance is 8s, our proposed algorithm performs similarly to the optimal one. However, when the variance is 15s, our algorithm's performance is much lower than the optimal solution. The result shows that the uncertainty degree matters regarding decision-making.

In the Diesel trace, the results are similar to those of the Gaussian distribution, as shown in Fig. 11. It indicates that waiting for RSUs is more like the Gaussian distribution. Since UMass is in the urban area, the result matches the location of UMass well. The result also indicates that our proposed algorithm can achieve a good performance. It is close to the optimal solution in different data size and utility decreasing speed. As for the cost, our proposed algorithm has better performance when the cost for the cellular network is large. The result also shows that always waiting for RSUs will lead to a low user satisfaction in most cases, as shown in Fig 11(b).

VI. Related Works

In this section, we summarize the two mainstream mobile offloading schemes: (1) the vehicles encountering prediction with RSUs. [6, 8, 11, 12], (2) the RSU deployment, aiming to minimize the encountering delay with RSUs or maximize the vehicle coverage with given number of RSUs [9, 13].

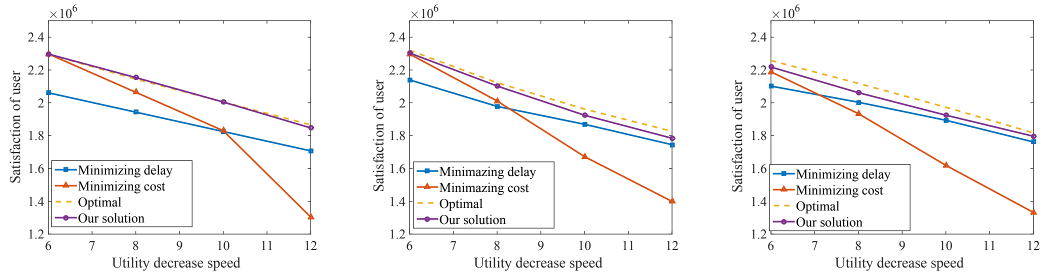
1) RSUs deployment problem: Due to the limited contact opportunity, the vehicle might need multiple RSUs to download the whole data, especially with the increasing content size. However, the existing works [9, 13, 14] simply assumed that the vehicles can get the request data through one RSU. Therefore, they focused on how to place RSUs so that these RSUs can cover as many vehicles' trajectories as possible. In [15], the author considered the multiple RSUs' content downloading problem. However, they assumed that the backhaul access is the bottleneck, and primarily focused their attention on the RSUs' pre-fetch and buffer replacement policy. However, in reality, the RSU network is built by different shops and different service providers. therefore, there are many scenarios where pre-fetching data might be impractical.

2) Mobile contact prediction: The accurate prediction of the encountering between vehicles and the RSUs in the existing RSU network is very important. The contact distribution varies in different scenarios, especially under the highly dynamic vehicular environment [11, 16–18]. To the best of our knowledge, we are the first to consider the correlated multiple RSUs' encountering estimation. The different estimation accuracy for multiple coming RSUs are considered in our model.

To our best knowledge, we are the first to consider the utility decay in the mobile offloading. In [6], the authors investigate the relationship between the access delay of messages and the users' satisfaction. In [8], the authors found the utility decay phenomenon by using the real data trace in the online social networks by experiment. Therefore, the time-sensitive data delivery in mobile offloading is meaningful.

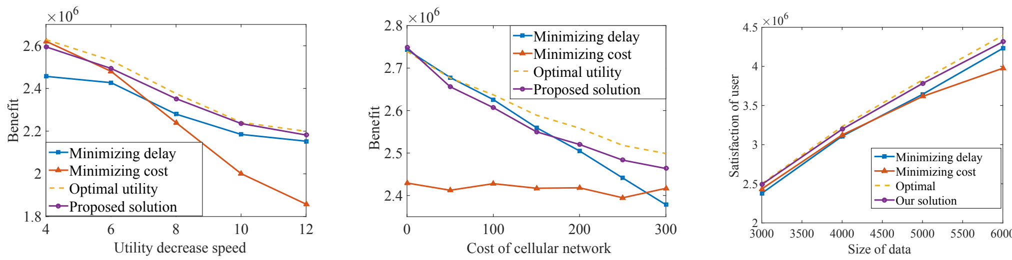
VII. Conclusion

In this paper, we focus on data offload scheduling in two interfaces. The different cost of these two interfaces and the delay of downloading is considered. The data utility will decay with time. A user would like to pay less money, and waits for a short time in reality. Then, we formulate the user's satisfaction maximization problem. Since the encountering between the vehicle and RSUs is opportunistic, we first propose a method to estimate the future event for multiple RSUs, then the vehicle



(a) Variance = 0s (b) Variance = 8s (c) Variance = 15s

Fig. 10. Performance comparison of our algorithm in different various degree (mean = 20s)



(a) Utility decay speed (b) Cost for cellular network (c) Size of data

Fig. 11. Performance comparison of our algorithm in Diesel Dataset

tries to find the best strategy based on the current estimation. Also, the vehicle might need to do re-decision regarding when to adjust the decision based on the actual situation. We do analysis regarding the problem on exponential and Gaussian distributions. The extensive experiments show that our algorithm achieves a good performance.

VIII. Acknowledgments

This work is supported in part by NSF grants CNS 1461932, CNS 1460971, CNS 1449860, IIP 1439672, and CNS 1156574.

References

[1] J. I. Feijoo and G. A. Gomariz, "New challenges on crossplatform digital."

[2] N. Cheng, N. Lu, N. Zhang, X. Shen, and J. W. Mark, "Vehicular wifi offloading: Challenges and solutions," *Vehicular Communications*, vol. 1, no. 1, pp. 13–21, 2014.

[3] M. Afanasyev, T. Chen, G. M. Voelker, and A. C. Snoeren, "Analysis of a mixed-use urban wifi network: when metropolitan becomes neapolitan," in *Proceedings of the ACM SIGCOMM*, 2008, pp. 85–98.

[4] E. Perahia and M. X. Gong, "Gigabit wireless lans: an overview of ieee 802.11 ac and 802.11 ad," *Mobile Computing and Communications Review*, vol. 15, no. 3, pp. 23–33, 2011.

[5] R. Goldsborough, "It's all about the connections," *Tech Directions*, vol. 72, no. 10, p. 12, 2013.

[6] X. Wang, M. Chen, Z. Han, D. O. Wu, and T. T. Kwon, "Toss: Traffic offloading by social network service-based opportunistic sharing in mobile social networks," in *Proceedings of the IEEE INFOCOM*, 2014.

[7] M. Atzmueller, A. Chin, C. Scholz, and C. Trattner, *Mining, Modeling, and Recommending'Things' in Social Media: 4th International Workshops, MUSE 2013, Prague, Czech Republic, September 23, 2013, and MSM 2013, Paris, France, May 1, 2013, Revised Selected Papers*. Springer, 2015, vol. 8940.

[8] H. Zhu, M. Li, L. Fu, G. Xue, Y. Zhu, and L. M. Ni, "Impact of traffic influxes: Revealing exponential intercontact time in urban vanets," *Parallel and Distributed Systems*, vol. 22, no. 8, pp. 1258–1266, 2011.

[9] A. B. Reis, S. Sargento, F. Neves, and O. K. Tonguz, "Deploying road side units in sparse vehicular networks: What really works and what does not," 2013.

[10] A. Balasubramanian, B. N. Levine, and A. Venkataramani, "Enabling interactive applications in hybrid networks," in *Proceedings of the ACM MobiCom*, 2008.

[11] B. Han, P. Hui, V. A. Kumar, M. V. Marathe, J. Shao, and A. Srinivasan, "Mobile data offloading through opportunistic communications and social participation," *Transactions on Mobile Computing*, vol. 11, no. 5, pp. 821–834, 2012.

[12] D. Zhang and C. K. Yeo, "Enabling efficient wifi-based vehicular content distribution," *Parallel and Distributed Systems*, vol. 24, no. 3, pp. 479–492, 2013.

[13] X. Li, C. Qiao, Y. Hou, Y. Zhao, A. Wagh, A. Sadek, L. Huang, and H. Xu, "On-road ads delivery scheduling and bandwidth allocation in vehicular cps," in *Proceedings of the IEEE INFOCOM*, 2013, pp. 2571–2579.

[14] T. Yan, W. Zhang, G. Wang, and Y. Zhang, "Access points planning in urban area for data dissemination to drivers," 2013.

[15] D. Zhang and C. K. Yeo, "Enabling efficient wifi-based vehicular content distribution," *Parallel and Distributed Systems*, vol. 24, no. 3, pp. 479–492, 2013.

[16] F. Malandrino, C. Casetti, C.-F. Chiasserini, and M. Fiore, "Offloading cellular networks through its content download," in *Proceedings of the IEEE SECON*, 2012.

[17] L. Song, D. Kotz, R. Jain, and X. He, "Evaluating location predictors with extensive wi-fi mobility data," in *Proceedings of the IEEE INFOCOM*, 2004.

[18] A. Balasubramanian, B. Levine, and A. Venkataramani, "Dtn routing as a resource allocation problem," *Computer Communi-*

cation Review, vol. 37, no. 4, pp. 373–384, 2007.
[19] H. Zheng, Y. Wang, and J. Wu, "Optimizing multi-copy two-hop routing in mobile social networks," in *Proceedings of the IEEE SECON*, 2014.
[20] V. V. Petrov, "Limit theorems of probability theory," 1995.

APPENDIX

A. Proof of Theorem 1

The encountering probability will decrease along with the time. The longer the vehicle waits, the smaller the expected satisfaction will be. Therefore, the vehicle only need to compare the utility of the current benefit and the expected benefit of the next second. If the vehicle decides to download data from the cellular network, the following equation should be satisfied based on Eq. 3.

$$\begin{aligned}&(U_0-c)\sum_{t=0}^{T}e^{-\lambda t}\cdot\lambda e^{-\lambda(t+1)}\\&>(U_0-c-a)\sum_{t=0}^{T}e^{-\lambda t}\cdot\lambda e^{-\lambda(t+1)}+\lambda ce^{-\lambda}.\end{aligned}$$

Here, we can use integration to replace the summation in order to simplify the above equation. The estimation error is bounded, and decreases along with the degree of discretization.

$$\begin{aligned}&(U_0-c)\int_{t=0}^{T}e^{-\lambda t}\cdot\lambda e^{-\lambda(t+1)}dt\\&>(U_0-c-a)\int_{t=0}^{T}e^{-\lambda t}\cdot\lambda e^{-\lambda(t+1)}dt+\lambda ce^{-\lambda}.\end{aligned}$$

After calculation, we get the following conclusion: $\frac{a}{2\lambda}>c$. Besides, due to the memoryless property of exponential distribution, the estimated inter-encountering time with a RSU is the same in the future. However, waiting causes the utility decrease. So, the vehicle should decide to use the cellular network at either the beginning, or never.

B. Proof of Theorem 2

When the decision-making interval is small enough, Eq.6 can be approximated by using the integration. The above approximation is bounded by the degree of discretization. Then, we get the following equation:

$$\begin{aligned}&\frac{2T^e(U_0-c)}{w^2}\int_{t=1}^{T^e}((1-\frac{t^{\beta+1}}{\beta+1})t^{\beta}\\&+\int_{t=T^e}^{2T^e}(\frac{(2T^e-t)^{\beta+1}}{\beta+1})(2T^e-t)^{\beta})dt.\end{aligned}\tag{14}$$

Eq. 7 can be approximated as

$$\begin{aligned}&\frac{T^e(U_0-c-a)}{w^2}(\int_{t=1}^{T^e}(1-\frac{t^{\beta+1}}{\beta+1})t^{\beta}\\&+\int_{t=T^e}^{2T^e}(\frac{(2T^e-t)^{\beta+1}}{\beta+1})(2T^e-t)^{\beta})+\frac{c}{w^2}(1-\frac{1}{\beta+1}).\end{aligned}\tag{15}$$

Comparing Eqs. 14 and 15, we get the result: $\frac{(T^e)^{\beta+1}a}{\beta}>c$.

C. Proof of Theorem 3

According to the Fourier transformation theory, the PDF of exponential distribution can be changed into:

$$\begin{aligned}\mathcal{F}\{f(t)\}&=\int_{-\infty}^{+\infty}f(t)e^{-jwt}dt\\&=\int_{-\infty}^{+\infty}\lambda e^{-\lambda t}e^{-jwt}dt=\frac{\lambda}{\lambda+jw}.\end{aligned}\tag{16}$$

Where j is the imaginary unit. Then, according to the [19],

$$\begin{aligned}&\mathcal{F}\{f(t_1,t_2,\ldots,t_k)\}=\prod_{i=i}^{k}\frac{\lambda_i}{\lambda_i+jw}\\&=\prod_{i=i}^{k}\lambda_i\cdot\sum_{i=1}^{k}\frac{1}{\prod_{m=1\&m\neq i}^{k}(\lambda_m-\lambda_i)}\frac{1}{\lambda_i+jw}\\&=\sum_{i=1}^{k}\frac{\prod_{i=i}^{k}\lambda}{\prod_{m=1\&m\neq i}^{k}(\lambda_m-\lambda_i)}\frac{1}{\lambda_i+jw}.\end{aligned}\tag{17}$$

Applying the inverse Fourier transformation to Eq. 17, we have

$$f(t_1,t_2,\ldots,t_k)=\sum_{i=1}^{k}\prod_{m=1\&j\neq i}^{k}\frac{\lambda_m}{\lambda_m-\lambda_i}e^{-\lambda_i t}.\tag{18}$$

When the n RSUs have the same λ, according to the central limit theorem [20], above equation can be approximated into

$$f(t_1,t_2,\ldots,t_k)\approx\frac{1}{\sigma_k\sqrt{2\pi}}e^{\frac{t-\mu_k}{2\sigma_k^2}},\tag{19}$$

where $\mu_k=\frac{k}{\lambda}$ and $\sigma_k=\frac{\sqrt{k}}{\lambda^2}$.

D. Proof of Theorem 4

Clearly, when t equals σ_k, the encountering probability fails into the $\frac{1}{e}$. So, we can say that the encountering will mainly happen during $[\bar{t}-\sigma,\bar{t}+\sigma]$. This Gaussian distribution can be regarded as the time shift of function $\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{t}{\sigma})^2}$. According to the Fourier transformation theory, if $f(t)=Ee^{-\frac{1}{2}(\frac{t}{\sigma})^2}$, we can get its Fourier transformation by the following equation

$$\begin{aligned}&\mathcal{F}\{f(t)\}=\int_{-\infty}^{+\infty}f(t)e^{-jwt}dt=\int_{-\infty}^{+\infty}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{t}{\sigma})^2}e^{-jwt}dt\\&=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}e^{-\frac{1}{2}(\frac{t}{\tau})^2}[cos(wt)-jsin(wt)]dt\\&=\frac{2}{\sigma\sqrt{2\pi}}\int_{0}^{+\infty}e^{-\frac{1}{2}(\frac{t}{\sigma})^2}[cos(wt)]dt=\sqrt{2}\cdot e^{-\frac{1}{2}(\frac{w\sigma}{2})^2}.\end{aligned}\tag{20}$$

Then, we can get the $\mathcal{F}\{f(t_1,t_2,\ldots,t_k)\}$ by multiplying the right part of Eq. 20 k times, the result is $2^{\frac{k}{2}}\cdot e^{-\frac{k}{2}(\frac{w\sigma}{2})^2}\cdot e^{-jwt_k'}$, where t_k', $t_k'=k\bar{t}$, is the expected encountering time with RSU k. If we denote $\sigma_k'=\sqrt{k}\sigma_k$, we can get the following equation

$$\mathcal{F}\{f(t-t_k')\}=2^{\frac{k}{2}}\cdot e^{-\frac{1}{2}(\frac{w\sigma_k'}{2})^2}.\tag{21}$$

According the symmetry property of Fourier transformation, the joint probability density function is:

$$f(t_1,t_2,\ldots,t_k)=\frac{1}{\sigma_k'\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{t-t_k}{\sigma_k'})^2}.$$