Opportunistic WiFi Offloading in Vehicular Environment: A Queueing Analysis

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Abstract—In this paper, we present an analytical framework for offloading cellular traffic by outdoor WiFi network in the vehicular environment. Specifically, we consider a generic vehicular user with Poisson data service arrivals to download/upload data from/to the Internet through the cost-effective WiFi network (want-to) or the cellular network providing full service coverage (have-to). Under this scenario, the WiFi offloading performance, characterized by offloading effectiveness, is analyzed in terms of desired average service delay which is the average time the data services can be deferred for WiFi availability. We establish an explicit relation between offloading effectiveness and average service delay by an M/G/1/K queueing model, and the tradeoff between the two is examined. We validate our analytical framework through simulations based on a VANET simulation tool VANETMobisim and real map data sets. Our analytical framework should be valuable for providing offloading guidelines to both vehicular users and network operators.

I. INTRODUCTION

It is evidenced that the demand for high-speed mobile Internet services has increased dramatically. A recent survey reveals that Internet access is predicted to become a standard feature of future motor vehicles [1]. Not surprisingly, cellular-based access technologies, such as 3G and Long Term Evolution (LTE), play a vital role in providing reliable and ubiquitous Internet access to vehicles, as the cellular infrastructure is well planned and widely available. However, the cellular network nowadays is straining to meet the current mobile data demand, and on the other hand, the explosive growth of mobile data traffic is no end in sight, resulting in an increasingly severe overload problem. It is reported that the connected mobile devices will become more than the world’s population in 2013, and the global mobile data will increase by 13 times in 2017, which will exceed one hundred exabytes [2]. Therefore, simply using the cellular network for vehicular Internet access may worsen the overload problem, and degrade the service performance of both non-vehicular and vehicular users.

With millions of hotspots deployed all over the world, WiFi can be a complementary solution to vehicular Internet access with low cost. The feasibility of WiFi for outdoor Internet access at vehicular mobility has been demonstrated [3]. The built-in WiFi radio or WiFi-enabled mobile devices on board can access the Internet when vehicles are moving in the coverage of WiFi hotspots, which is often referred to as the drive-thru Internet [4]. Recent advances in Passpoint/Hotspot 2.0

1We interchangeably use the terms “vehicle” and “vehicular user” in this paper.

...make WiFi more competitive to provide secure connectivity and seamless roaming [5]. For stationary or slow moving users, WiFi serves as one of the primary offloading technologies [6]. By delivering data originally targeted for cellular networks by WiFi, termed WiFi offloading, the congestion of cellular networks can be alleviated. It has been shown that around 65% of the cellular traffic can be offloaded by merely switching from the cellular network to WiFi when the WiFi connectivity is available (on-the-spot offloading) [6]–[8]. If data services can be deferred for some time (e.g., up to one hour) until WiFi connectivity becomes available, above 80% of the cellular traffic can be offloaded (delayed offloading). Obviously, the offloading performance is surprisingly good in stationary/low-mobility scenarios. In a vehicular environment, vehicles signal to nearby WiFi access points (APs) when traveling along a road, so that the cellular traffic can be delivered to vehicles through the drive-thru Internet in an opportunistic manner. Such an opportunistic WiFi offloading has unique features.

- A relatively small volume of data can be delivered to a vehicle in each drive-thru, due to the short connection time with WiFi APs; and
- The offloading performance can be significantly improved if the data service can tolerate a certain delay, as vehicles with a high speed can have multiple drive-thru opportunities in a short future.

To the best of our knowledge, the offloading performance in the vehicular environment remains open in the literature. In this paper, we aim at theoretically analyzing the performance of vehicular WiFi offloading with the delayed offloading strategy. We consider a generic vehicular user having randomly arrived data services, either to download data (e.g., E-mail attachment and YouTube video clip,) or upload data (e.g., WeChat messages and online diagnosis data) from/to the Internet. The data services can be fulfilled through either WiFi network (want-to) or the cellular network (have-to). The cellular network is considered ubiquitous and WiFi APs are sparsely deployed. The offloading performance is characterized by average service delay and offloading effectiveness. Average service delay is defined as the average duration from the arrival of a data service request to the fulfillment of the service through WiFi network, which is mostly contributed by the waiting time for the WiFi availability and is the “price” of using delayed offloading. Offloading effectiveness is defined as the long-term proportion of data services fulfilled
through WiFi network under the requirement of a desired average service delay. Intuitively, if the data services can be deferred for a longer time (i.e., relaxing the requirement on the average service delay), more data services can be offloaded by WiFi network, yielding a higher offloading effectiveness. From a user’s perspective, however, the increased average service delay would somehow reduce the user satisfaction on data services. Our analytical framework provides the relation between these two metrics and the tradeoff is examined. In specific, we present a queueing analysis of offloading performance in a vehicular environment. We model the arrivals and fulfills of data services of a vehicular user as an M/G/1/K queue, with M characterizing the arrival process of data service requests waiting to be served by drive-thru Internet, and system capacity K controlling the average service delay. If a service request arrives with a full queue, it will be served directly via the cellular network to avoid a longer delay than the expected service delay. As the data transmission with WiFi APs is in an opportunistic manner, the queue departure process (i.e., the process of data transmission or service fulfillment) is characterized by the effective service time (EST) which is the duration from the transmission of the first bit of a data service to the service request is fulfilled. The probability distribution of the EST is theoretically derived using Laplace-Stieltjes transform (LST). Based on the statistics of the EST, the offloading effectiveness and average service delay and their relation are given. We validate our analytical framework through simulations based on a VANET simulation tool VANETMobisim and real map data sets.

**Implementation of our analytical framework:** For vehicular users, the explicit relation between offloading effectiveness (how much Internet access cost can be saved) and average service delay (how much service degradation the user is willing to tolerate) can provide offloading guidelines. For example, the on-board smart offloading engine (a mobile App) can do intelligent network selection based on the user’s preference on service delay. On the other hand, due to the razor-sharp competition, many network operators are looking for new ways to cut spending and stand out in the market. Network operators, such as AT&T, NTT Docomo and China Mobile, are starting to deploy carrier WiFi to offload cellular networks and profit from the new business model. First of all, our results give the network operators more incentives to deploy outdoor WiFi network as the offloading effectiveness is notable in vehicular environments. Moreover, our framework can provide network operators with some guidance on WiFi deployment (e.g., the density of WiFi APs) according to the theoretical offloading effectiveness. In a nutshell, our analytical framework can be applied in practice not only for vehicular users to make offloading decisions, but also for network operators to evaluate AP deployment strategies, make offloading-related pricing models, and so forth.

The remainder of the paper is organized as follows. Section II studies the literature of drive-thru Internet and vehicular WiFi offloading. Section III describes the system model. Section IV derives the probability distribution of the EST. Section V analyzes the queue and the tradeoff between offloading effectiveness and average service delay. Section VI evaluates the analysis by real road map based simulation. Section VII concludes the paper.

**II. RELATED WORK**

**A. Drive-Thru Internet**

Drive-thru Internet can provide Internet access to moving vehicle via WiFi APs. Different from non-vehicular users accessing WiFi, drive-thru Internet has some unique characteristics, such as short and intermittent connectivity, unreliable transmission, fluctuating channels, etc. To characterize and evaluate the performance of drive-thru Internet, experiment-based measurements can be found in [3], [4]. It is shown that the average connection period (vehicle is being connected to any AP) is about several to tens of seconds, and the average inter-connection period (vehicle is not connected to any AP) is about tens of seconds. The average volume of data that can be transferred within a drive-thru access is from several MB for IEEE 802.11b to tens of MB for IEEE 802.11g.

**B. Vehicular WiFi Offloading**

Vehicular WiFi offloading uses intermittent drive-thru Internet opportunities as a supplement to cellular networks to transfer data, while considering the cost effectiveness, delay tolerance, user satisfaction, etc. In [9], an offloading scheme called Wiffler is proposed to determine whether to defer applications for the WiFi connectivity instead of using cellular networks right away. In [10], a protocol called oSCTP is proposed to offload the 3G traffic through WiFi network and maximize the user’s benefit. The philosophy of oSCTP is to use WiFi and 3G interfaces simultaneously if necessary, and schedule packets transmitted in each interface every interval.

**III. SYSTEM MODEL**

In this section, we present the system model, including communication paradigm, mobility of vehicles, and queuing model of vehicular users’ data services. Based on the system model, we can evaluate the performance of vehicular WiFi offloading by analyzing the M/G/1/K queue.

**A. Communication model**

In this paper, we consider an urban area as a bounded region with WiFi APs randomly deployed. Vehicular users access drive-thru Internet when possible since it tends to have a higher data rate and less cost than cellular networks. Automatic rate adaptation is widely used in the stock WiFi technology according to the signal strength. However, for simplicity, we consider the communication data rate between APs and vehicles is identical and denoted by R. Assume the idle MAC is employed where channel access time is fairly shared by the nearby vehicular users. To account for real MAC behaviors, a MAC throughput effective factor η is considered, which indicates the theoretical maximum portion of throughput considering the protocol overhead, e.g., η = 45.5% for 11 Mbps bit rate of IEEE 802.11b [11]. Thus, the data rate of a tagged vehicular
user $V$ can be represented by $r = \frac{nR}{\eta + \gamma}$, where $n$ is the number of neighboring vehicular users of $V$ connected to the same AP. With the second order Taylor approximation, the average data rate of an arbitrary vehicular user connected to an AP can be approximated by

$$\bar{r} = r|_n + \frac{1}{2} \text{Var}(n) \frac{d^2 r}{dn^2}|_n,$$

where $\bar{n}$ and $\text{Var}(n)$ are the mean and variance of $n$, respectively [12].

**B. Mobility model**

The high mobility of vehicles may lead to short and intermittent drive-thru access opportunities. We model the mobility of $V$ by an on-off process, with on-state and off-state denoting the situation that $V$ is within and out of the coverage area of an AP. In on-state, $V$ can transmit data through the AP with an average data rate $\bar{r}$; and in off-state, the transmission rate is assigned to zero, since $V$ is out of the coverage area of any AP. Due to the random locations and coverage of open APs, we model the sojourn time of both on-state and off-state by the unpredictable and memoryless exponential distribution, with parameter $\lambda$ and $\mu$, respectively [12], as shown in Fig. 1.

**C. Queueing model**

We model the arrivals and fulfillments of data services of a vehicular user as an $M/G/1/K$ queue, as shown in Fig. 2. A data service request arrives at the queue with a random inter-arrival time which follows the exponential distribution with mean $1/\gamma$. In other words, the arrival process of the queue is Poisson process. We also consider that the sizes of service requests are identical, denoted by $S$. The departure process of the queue is not Markovian due to the service interruption. If a service request cannot be fulfilled within one drive-thru, it will wait for more drive-thru opportunities until fulfillment. We model the departure process by the EST which follows a general distribution. The EST $t_e$ composes of the service time $x$, and time of server interruptions, i.e., when the vehicle is out of the coverage area of any AP. The queue capacity $K$ represents the maximum number of service requests in the system, and thus the queue buffer length is $K - 1$. We consider patient customer-type of queue, which means that if one service request enters the queue, it will wait until fulfillment. However, if a service arrives with a full queue, it expects that the delay would exceed the desired service delay. Thus, the service request will be directly served by the cellular network. With the queueing model and probability distribution of the EST which is obtained in the next section, the queue performance can be evaluated, with the average service delay and offloading effectiveness analyzed.

**IV. DERIVATION OF EFFECTIVE SERVICE TIME**

We characterize the departure process and derive the probability distribution of the EST in this section.

Since there is no data transmission when a vehicle is outside the coverage area of any WiFi AP, the queue server is subject to intermittent interruptions. Let $t_e(x)$ denote the EST of an arbitrary request with service time $x$, whereas $x$ is assumed to follow the exponential distribution with parameter $\lambda_s = \frac{\lambda}{2}$, as in [12]. Since $t_e(x)$ composes of $x$ and the time of server interruptions, we then have

$$t_e(x) = \begin{cases} x & H_\lambda \geq x \\ H_\lambda + H_\mu + T(x - H_\lambda) & H_\lambda < x, \end{cases}$$

where $H_\lambda$ and $H_\mu$ are the length of an arbitrary on-state period and off-state period, which follow the exponential distribution with mean $1/\lambda$ and $1/\mu$, respectively. According to [13], the EST can be analyzed using LST. Let $T_e(\xi)$ be LST of the probability density function (PDF) of $t_e(x)$, and based on [13]:

$$T_e(\xi) = \int_0^\infty f(x) e^{-\xi} \frac{dx}{\eta + \gamma} = \int_0^\infty \lambda e^{-\lambda x} e^{-\xi} \frac{dx}{\eta + \gamma} = \frac{\lambda_s}{\xi + \lambda - \lambda V_\mu(\xi) + \lambda_s},$$

where $V_\mu(\xi) = \frac{\mu}{\mu + \xi}$ is LST of the PDF of the length of an arbitrary off-state period. We can then obtain the expectation of the EST by

$$E[t_e] = -\frac{dT_e(\xi)}{d\xi} |_{\xi=0} = \frac{\lambda_s}{\xi + \lambda - \lambda V_\mu(\xi) + \lambda_s} |_{\xi=0} = \frac{1}{\lambda_s} \frac{\lambda_s}{1 + \frac{\lambda}{\mu}}.$$
From (4), \( \mathbb{E}[t_e] \) is affected by server interruptions in the way that \( \mathbb{E}[t_e] \) increases with the increase of interruption occurrence rate \( \lambda \) and mean interruption duration \( \frac{1}{\mu} \).

To analyze the M/G/1/K queue, we then derive the PDF of the EST, which is denoted by \( f_e(t) \). Utilizing the inverse transform of LST, we have

\[
f_e(t) = L^{-1}(T_e(\xi)) = \frac{1}{2\pi} \lim_{\delta \to 0} \int_{-\infty}^{\infty} e^{\xi t} T_e(\xi) d\xi,
\]

where \( \theta \) is a real number that is greater than the real part of all singularities of \( T_e(\xi) \). The singularities of \( T_e(\xi) \) can be obtained by making the denominators equal zero, i.e.,

\[
\xi_{\text{sin}} = \{\xi | \xi + \mu = 0\} \cup \{\xi | \xi + \lambda - \frac{\mu}{\mu + \xi} + \lambda_s = 0\}.
\]

Simplifying (6), we can get \( \xi_{\text{sin1}} = -\mu \) and \( \xi_{\text{sin2}} = \frac{1}{2} (-(\lambda + \lambda_s + \mu) \pm \sqrt{(\lambda + \lambda_s + \mu)^2 - 4\lambda_s \mu}) \) (if \( \xi + \lambda - \frac{\mu}{\mu + \xi} + \lambda_s = 0 \) has solution(s).) Since all singularities of \( T_e(\xi) \) are smaller than zero, we can set \( \theta = 0 \). Using Bromwich inversion integral [14] and the fact that \( \theta = 0 \), we have

\[
f_e(t) = 2 \int_0^\infty \frac{\Re e^{i \lambda u} \cos(ut) du}{\pi} + 2 \int_0^\infty \frac{\Re e^{i(\lambda u + \mu u + \mu \lambda_s) \cos(ut) du}}{\pi}.
\]

Since integration (7) is difficult to calculate, we use Fourier-Series method and the trapezoidal rule to obtain \( f_e(t) \) for any given \( t_e \) [14].

\[
f_e(t) \approx f_e^h(t) \equiv \frac{he^{\theta t}}{\pi} T_e(\theta) + \frac{2he^{\theta t}}{\pi} \sum_{k=1}^{\infty} \Re e^{i(k \lambda t)} \cos(kht).
\]

Some results of the EST are shown in Fig. 3(a), with the effects of \( \lambda_s, \lambda, \text{ and } \mu, \) respectively. It can be seen that the EST increases with the decrease of \( \lambda_s \) and \( \mu \), and with the increase of \( \lambda \). Smaller \( \lambda_s \) indicates a larger request service time \( x \), and thus a larger EST with server interruptions. On the other hand, because a larger \( \lambda \) and a smaller \( \mu \) indicate more frequent and longer interruptions, respectively, the EST then increases. To validate the accuracy of the EST derivation, the theoretical results are compared with the simulation results in Fig. 3(b). In the simulation, a virtual queue with exhaustive customer arrivals and server interruptions is considered. From the figure, it can be seen that the curves of theoretical and simulation results closely match each other, which demonstrates the accuracy of the analysis.

V. ANALYSIS OF QUEUEING SYSTEM AND OFFLOADING PERFORMANCE

Given the probability distribution of the EST obtained in (8), we can evaluate the performance of offloading by analyzing the M/G/1/K queue. Because the EST is not exponential, we utilize the imbedded Markov chain of system states at the time instant \( t_d \), which is the time instance of service request \( i \)'s fulfillment, to analyze the queue [15].

A. Queue analysis

Let \( n_i \) be the number of requests left in the system seen by the \( i \)th request when it leaves the system, and \( \chi_i \) be the number of arrivals during the EST of request \( i \). We then have

\[
n_{i+1} = n_i - U(n_i) + \chi_i + 1,
\]

where \( U(n_i) \) is the unit step function where \( U(n_i) = 0 \) if \( n_i = 0 \), and \( U(n_i) = 1 \) otherwise. Then, the transition probabilities at departure instances are defined as

\[
p_{d,j,k} = P\{n_{i+1} = k | n_i = j\} \quad 0 \leq j, k \leq K - 1.
\]

Let \( \omega_k \) be the probability of \( k \) arrivals during the EST of an arbitrary service request. Using the Poisson arrival property, we can get

\[
\omega_k = \int_{t=0}^{\infty} \frac{(\gamma t)^k}{k!} e^{-\gamma t} f_e(t) dt,
\]

where \( \gamma \) is the arrival rate of service requests and \( f_e(t) \) is the PDF of the EST given in (8). Thus, we can easily obtain the \( K \times K \) transition probability matrix as

\[
P_{d,j,k} = \begin{bmatrix}
\omega_0 & \omega_1 & \omega_2 & \cdots & \omega_K - 2 & \sum_{m=K-1}^{\infty} \omega_m \\
\omega_0 & \omega_1 & \omega_2 & \cdots & \omega_K - 2 & \sum_{m=K-1}^{\infty} \omega_m \\
0 & \omega_0 & \omega_1 & \cdots & \omega_K - 3 & \sum_{m=K-2}^{\infty} \omega_m \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & \omega_0 & 1 - \omega_0
\end{bmatrix}
\]

Let \( p_{d,k} \) be the equilibrium state probabilities at departure instants, which can be calculated by

\[
p_{d,k} = \sum_{j=0}^{K-1} p_{d,j} p_{d,j,k} \quad k = 0, 1, \cdots, K - 1
\]

\[
\sum_{k=0}^{K-1} p_{d,k} = 1 \quad (\text{Normalisation Condition}).
\]

Let \( p_k, k = 0, 1, 2, \cdots, K \) be the steady-state probabilities of the system states, and \( P_{\text{BL}} = p_K \) be the blocking probability. Based on Poisson arrivals see time averages (PASTA) property, \( p_k \) can be calculated by (15) [15].

\[
p_k = (1 - P_{\text{BL}}) p_{d,k} \quad k = 0, 1, 2, \cdots, K - 1.
\]
The traffic intensity $\rho$ and the actual traffic intensity $\rho_c$, considering queue blocking are given by $\rho = \gamma \mathbb{E}[t_e]$ and $\rho_c = (1 - P_B) \rho$, respectively. It is straightforward that $p_0$, the steady-state probability that the queue is empty, should be equal to $1 - \rho_c$. Then, we have

$$P_B = 1 - \frac{1}{p_{d,0} + \rho},$$

by using (15) for the case $k = 0$ and the fact that $p_0 = 1 - \rho_c$. Using (15) and (16), we have

$$p_k = \frac{1}{p_{d,0} + \rho} p_{d,k} \quad k = 0, 1, 2, \ldots, K - 1.$$  

### B. Offloading performance

Using (16) and (17), the mean number of customers $N$ in the system can be represented as a function of $K$:

$$N(K) = \sum_{k=0}^{K} k p_k = \frac{1}{p_{d,0} + \rho} \sum_{k=0}^{K-1} k p_{d,k} + K (1 - \frac{1}{p_{d,0} + \rho}).$$  

(18)

And the average total time in the system, i.e., average service delay, is also a function of $K$ and can be calculated using Little’s law:

$$W(K) = \frac{N}{1 - P_B} = \frac{\sum_{k=0}^{K-1} k p_{d,k} + K (p_{d,0} + \rho - 1)}{\gamma}.$$  

(19)

We use unblocked rate $(1 - P_B)$ to measure the offloading effectiveness $\mathcal{E}$. For the system with queue capacity $K$, request size $S$, and statistics of on and off periods, $\lambda$ and $\mu$, the offloading effectiveness can be calculated by

$$\mathcal{E} = 1 - P_B = \frac{1}{p_{d,0} + \rho}.$$  

(20)

Thus, the blocked services requests, with portion $P_B$ of the total traffic, should be transmitted using cellular networks. To show the offloading capability for a given traffic load, define average offloading throughput for traffic load $\gamma$ as

$$\Omega = \gamma S \mathcal{E} = \frac{\gamma S}{p_{d,0} + \rho}.$$  

(21)

It can be seen that for a given $\gamma$, a larger $\mathcal{E}$ generally leads to a larger $\Omega$. However, for an overload queue ($\rho > 1$) due to the heavy traffic, there is an upper bound of the average offloading throughput, denoted by $\Omega_m$. For an overload queue, we can calculate $\Omega_m$ by setting $p_0 = 0$ since the server keeps busy serving the requests. Because the average service time of a request is its mean EST, calculated by (4), we can obtain the upper bound of the average offloading throughput as

$$\Omega_m = S \mathbb{E}[t_e] = \frac{\bar{r}}{1 + \frac{\bar{r}}{\mu}}.$$  

(22)

As discussed above, there is a tradeoff between average service delay and the offloading effectiveness. Such a tradeoff can be analyzed using the results of the queueing model. There are two issues that vehicular users and network operators may be interested in: 1) Given a certain average service delay, how much data can be offloaded; and 2) To offload a certain amount of data, how much is the least average delay that the users should tolerate. For 1), let the average service delay that users can tolerate be $W_U^*$, the corresponding $K^*$ is

$$K^* = \max \{ K | W(K) \leq W_U^* \}.$$  

(23)

Then, the offloading effectiveness $\mathcal{E}^*$ can be calculated by

$$\mathcal{E}^* = 1 - P_B|_{K=K^*} = \frac{1}{p_{d,0} + \rho}|_{K=K^*}.$$  

(24)

For 2), the solution is similar by setting a target offloading effectiveness $\mathcal{E}_U^*$.

### VI. Simulation Results

In this section, we evaluate our proposed queueing model, and demonstrate the performance of vehicular WiFi offloading and the tradeoff between offloading effectiveness and average service delay. The simulation is carried out in a 2.0 km $\times$ 2.0 km region road map of the downtown area of Washington D.C., USA. WiFi APs are randomly deployed with the coverage radius of 100 meters. There may exist overlapping of WiFi coverage areas. However, we show that low-level overlapping has little impact on the offloading performance. The street layout and AP locations are shown in Fig. 4. Each street segment has two lanes with the bidirectional vehicle traffic. VANETMobisim [17] is used to generate the mobility traces of 300 vehicles. With 50 deployed APs, the parameters can be obtained from the simulation, as $1/\lambda = 31.5$ s, $1/\mu = 52.09$ s, $\bar{n} = 1.54$, and $\text{Var}(n) = 7.71$. It is considered that vehicles can transmit through WiFi immediately when they move into the coverage area, which is already supported by advanced WiFi technologies, e.g., HotSpot 2.0. With 802.11b bit rate 11 Mbps, $\bar{r} = 4.32$ Mbps using (1). Note that our proposed analytical model can be applied to other WiFi technologies if the average data rate is known. The service request size $S$ is set to 5 MB, which is the size of a typical MP3 file.

The offloading effectiveness $\mathcal{E} = 1 - P_B$ is shown in Fig. 5(a). It can be seen that with a larger queue capacity $K$, the offloading effectiveness $\mathcal{E}$ increases, which means that a larger
Table I
MAXIMUM UTILITY OF VEHICULAR USERS

<table>
<thead>
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<th>[K, U_{ms}]</th>
<th>γ = 0.03</th>
<th>γ = 0.045</th>
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<td>[8, 0.65]</td>
<td>[6, 0.52]</td>
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VII. Conclusion

We have theoretically investigated the performance of vehicular WiFi offloading. We have modeled the arrivals and fulfillments of data services of a vehicular user as an M/GI/K queue, derived the probability distribution of the effective service time and analyzed the average service delay and offloading effectiveness by the queueing analysis. Simulation results have validated the analysis, and shown the relationship between average service delay and offloading effectiveness.

For our future work, we will study the vehicular offloading in scenarios with planned deployment of APs, and develop offloading schemes utilizing both WiFi and multi-hop vehicle-to-vehicle communications.

REFERENCES