# Vehicle-Density-Based Adaptive MAC for High Throughput in Drive-Thru Networks 

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#### Abstract

Drive-thru Internet has become a popular solution vehicular Internet access. However, the quality-of-service provisioning for high-data-rate drive-thru Internet services poses significant challenges upon medium access control (MAC) in a large-scale and highly dynamic vehicular environment. In this paper, to achieve high throughput in drive-thru Internet, we exploit the mobility interdependency between neighboring vehicles and propose a density-adaptive MAC protocol by predicting the vehicle-density dynamics. Specifically, to predict the vehicle-density fluctuations in the drive-thru Internet scenario, we leverage Navier-Stokes equations to characterize the mobility interdependence and the dynamically waving vehicle-density which can be observed from the simulated vehicle traces in VISSIM. In tune with the dynamic vehicle-density, we propose an enhanced MAC protocol to dynamically adjust the contention window (CW) setting in order to improve the throughput. Extensive simulations validate the effectiveness of the utilized mobility model, and demonstrate the efficiency of the proposed MAC protocol in improving the overall resultant system throughput.


Index Terms-Drive-thru Internet, dynamic vehicle density, medium access control (MAC).

## I. Introduction

VEHICULAR communications to the Internet via access points (APs), i.e., drive-thru Internet [1], have received considerable attentions. With Internet access, vehicles can enjoy precious infotainment applications, e.g., path-planning services to avoid the traffic jam via Google Maps [2] . However, with the demand of a large population of vehicles, the available throughput for individual vehicle is insufficient in delivering media-rich Internet contents. especially when the vehicles are highly mobile leading to intermittent connections with APs. Moreover, due to high mobility, the association time, i.e., the time required for an AP to detect a vehicle moving into its coverage range, may be larger than the vehicle sojourn time within an AP's coverage range, resulting in missing the connection with the AP [3]. Therefore, it is important to investigate the throughput performance of IEEE 802.11 APs, the realistic high-speed large-scale drive-thru Internet scenario.

The literature [1], [4]-[6] has studied the throughput performance of drive-thru Internet. Ott and Kutscher [1] show

[^0]that by exploiting IEEE 802.11b hardwares for vehicles, an individual vehicle at a velocity of $80 \mathrm{~km} / \mathrm{h}$ can obtain 9 MB data when passing by an AP. To improve throughput for the scalable drive-thru Internet, Luan et al. [4] guide a contention-based distributed coordination function (DCF) by configuring smaller contention window (CW) size for vehicles that are closer to the AP. Han et al. [5] propose a throughput analytical model with an enhanced DCF intended for heterogeneous traffic conditions. Tan, et al. [6] derive analytical Markov chain models to characterize the average and the distribution of the number of bytes downloaded by a vehicle. For all the above works, the vehicledensity is assumed to be constant based on a fixed arrival rate of the vehicle traffic flow; however, vehicle-density is timevarying especially in the high vehicle-density scenario. The high fluctuations impact much on the communication performance [7], [8]. Thus, the constant vehicle-density assumption on average sense [9] is not accurate enough in realistic vehicular scenarios. Furthermore, all the existing works ignore the association time between vehicles and APs; however, this association time is nonneglectable and critical for a vehicle in order to properly configure communications with APs in realistic vehicular networks [10].

To illustrate the vehicle-density in the realistic scenarios, we emulate the vehicle traffic in a highly realistic vehicle simulator-VISSIM [11]-on a highway. Fig. 1 shows that the vehicle-density varies with not only time but also location. Specifically, vehicles may be stuck in the traffic for a while leading to a high vehicle-density and afterward keep moving smoothly, e.g., nearby the freeway exit (i.e., the intersection) which is the typical location of the AP; in addition, the heavy vehicle-density may spread backward with location (see the red circle noted in Fig. 1). Furthermore, the technical report in [12] from U.S. Department of Transportation Federal Highway Administration demonstrates that traffic waves of a group of vehicles show typical fluctuations in group length and frequent events of condensation waves starting at the leading vehicle and traveling backward within the group. In light of the fact that the fluctuations of vehicle-density can impact much on the communication performance especially in the high-density scenario [7], [8], we aim to design a vehicle-density-aware MAC to fully utilize the cherished bandwidth resources based on the density dynamics and mobility interdependence of vehicles in a dense scenario.
In this paper, to investigate the observed fluctuating vehicledensity, an accurate and realistic mobility model based on Navier-Stokes equations is first supplied to describe the dynamics and interdependence of vehicle mobility for vehicle-density


Fig. 1. 3-D vehicle traffic illustrations of the fluctuating vehicle-density on a highway in VISSIM. (a) At $t=600 \mathrm{~s}$. (b) At $t=625 \mathrm{~s}$. (c) At $t=650 \mathrm{~s}$.
prediction over both time and location. Specifically, we utilize a stochastic microscopic mobility model by stochastic calculus to describe dynamic and dependent mobility characteristics of a group of vehicles. The distributions of vehicle-density and velocity over both time and position are derived to predict the vehicle-density. In this model, to reveal the mobility interdependence between neighboring vehicles, virtual forces, originally defined in biology, ${ }^{1}$ are applied so that the fluctuating vehicle-density with both time and location can be described based on a stochastic microscopic mobility model by stochastic calculus. Furthermore, with the utilized mobility model, the vehicle-density of a position at one time, e.g., at the location of an AP, can be used to estimate the vehicle-density fluctuations of any other position, e.g., the location of the AP in front, at any other times.

In addition, based on the predicted fluctuating vehicledensity and the collected traffic information by loop detectors or multiple cameras, we can unveil the impacts of dynamically waving vehicle-density on the resultant system throughput and the optimal configuration of MAC, and further design a vehicle-density-aware MAC to improve throughput performance, for infotainment applications. Here, the original vehicle-density is collected by loop detectors or multiple cameras, and the vehicle-densities (which may fluctuate with both location and time) within the coverage range of APs can be further predicted fully based on the derived mobility model. In other words, the association time to detect a vehicle moving into an AP is not necessary in our designed framework. Thus, the association times can be reduced and/or saved through this prediction mechanism. To this end, we aim at addressing the following questions in this paper. 1) How does the mobility affect vehicle-density and how to predict the vehicle-density at particular locations? 2) How to utilize the predicted vehicledensity to improve throughput? The contributions of this paper are threefold.

1) Based on currently collected velocity and location information via loop detectors/multiple cameras, a stochastic microscopic mobility model by stochastic calculus is utilized to reveal the dynamically waving vehicle-density in a drive-thru Internet scenario. This model can be used for dynamic vehicle-density prediction on particular locations, e.g., the location of an AP.

[^1]2) With the vehicle-density prediction, we design a vehicle-density-aware MAC to improve the overall resultant system throughput for infotainment applications. By dynamically adjust the CW size in DCF, MAC is intelligently designed in tune with the dynamic vehicle-density by a traffic server in a real-time manner; by adopting the designed MAC to determine the channel access opportunity for an individual vehicle, an AP can fully utilize the network resource.
3) We carry out extensive simulations to validate the effectiveness of our utilized mobility model and efficiency of the proposed MAC protocol. Simulation results confirm that our proposed MAC is able to improve the system throughput and save the access time in a timely, efficient, and global way.
This paper is organized as follows. Section II surveys the related work. The system model and the formulation of the proposed mobility model are discussed in Sections III and IV, respectively. In Section V, the proposed MAC is presented based on the defined mobility model. Section VI demonstrates the performance of the proposed strategy by simulations. Section VII concludes this paper.

## II. Related Works

In the literature, most of the analytical mobility descriptions of vehicles are based on an average sense following a Poisson distribution which is nondependent and memoryless [15]-[17]. In a sparse scenario, this mobility model is accurate enough for performance analysis. However, in a dense scenario, e.g., the highway scenario nearby the exit point at peak time, the mobility between vehicles is dependent. For example, a car following model [18], [19] and a Markov spacing model [20], [21] have been used to describe the dependence of vehicle's mobility. However, these models do not reveal the relationship between mobility and the change of vehicledensity, which can be utilized for vehicle traffic prediction. Thus, to reveal the dependence among vehicles in a dense vehicular scenario, a novel mobility model, which can describe the vehicle-density fluctuations with both time and position, is required.

On the other hand, to improve the system throughput performance, existing works [22], [23] adjust CW size based on transmission rates. In [22], only nodes with the best SNR are allowed to transmit in the drive-thru Internet. In [23], by assigning better SNR nodes with the relatively small CWs and high-packet transmission rates, the system throughput could be further enhanced. The vehicle-density was assumed to be stable


Fig. 2. Hybrid network architecture.
with an average value; however, vehicle-density can dynamically fluctuate with time and locations, which can impact much on the communication performance especially in the high vehicle-density scenario [7], [8]. So far, little has done to study the impact of a more accurate and realistic dynamically fluctuating vehicle-density on throughput and the predictably adaptive MAC protocol to the dynamic vehicle-density. Therefore, in this work, we provide a predictable vehicle-density-aware DCF as the MAC protocol based on the proposed thorough theoretical mobility analysis.

## III. System Models

Aiming at providing adaptive MAC protocol for vehicles via the dynamic vehicle-traffic density, we introduce the network architecture, followed by the defined transmission model.

## A. Hybrid Network Architecture

Fig. 2 shows the components of the architecture in a considered drive-thru Internet scenario, consisting of vehicles, loop detectors or multiple cameras, a traffic server, and APs on road sides.

Consider that a set of vehicles $\mathbb{V}$ move along a road, (e.g., a highway with multilanes in one direction ${ }^{2}$ in Fig. 2), each equipped with on-board communication facilities [e.g., onboard units (OBUs)] for vehicle-to-infrastructure (V2I) communications.

A limited number of loop detectors or multiple-cameras are deployed due to the budget. Via loop detectors or multiplecameras, the traffic information can be collected (e.g., every 15 min ) and delivered to a traffic server through the wired connections. In the traffic server, the average traffic information (e.g., vehicle-density) is calculated for that time period. Then, based on the collected traffic information, the traffic server can calculate and predict the dynamic vehicle-densities with both time and position, through our derived mobility model. In our paper, time is partitioned into periods, and the duration

[^2]of each period determines the accuracy and computational complexity of mobility prediction according to the utilized mobility model. A shorter duration will lead to more accurate mobility prediction but higher computational complexity, and vice versa. Moreover, based on the proposed mobility model (see Section IV) and the calculated average traffic information, the traffic server is capable of predicting the dynamic traffic information at the AP (or any position along the highway) and performing online MAC protocols to provide optimized DCF decisions for vehicles in need of communication in a predictive manner.

Through deploying APs along highway, V2I communication is enabled based on IEEE 802.11b [1]. That is, when a vehicle moves into the transmission range of an AP, the vehicle can be scheduled to transmit information, e.g., upload data packets, to the AP following the specific MAC protocol. Note that we focus on the MAC layer under perfect channel conditions (i.e., no transmission errors and no hidden terminals) [4]. Since the APs are also connected to the traffic server, uploaded packets can further be delivered to the traffic server.

Therefore, as shown in Fig. 2, to design a vehicle-densityadaptive MAC protocol, the communication process in the considered drive-thru Internet scenario can be divided into three steps, which are: 1) the loop detectors or multiple-cameras deliver the collected vehicle-traffic information to the traffic server; the traffic server analyzes the information, predicts the vehicle-density trend, and decides the adaptive CW size for individual vehicles at the location of any AP; 2) the traffic server forwards the decision of adaptive CW setting to the AP of interest, and the AP sets the corresponding CW size for individual vehicles in a predictive manner; and 3) vehicles upload packets to the AP based on the received adaptive CW setting, by IEEE 802.11 b-based V2I communication, once vehicles move into the coverage range of that AP. Since the DCF is configured in a predictive manner based on the utilized mobility model, based on the shared vehicle information from the front AP instead of detecting vehicles again, the time of vehicle association with the following AP can be saved.

## B. DCF in the Drive-Thru Internet

Through DCF, the transmission of vehicle packets is traditionally decided by the availability of a channel. That is, when a channel is idle for a period of distributed interframe space (DIFS), the transmission stirred by a vehicle may be scheduled; otherwise, the vehicle will wait until the end of the in-progress transmissions. To prevent multiple vehicles from collisions due to possibly simultaneous transmissions, DCF applies a collision avoidance (CA) mechanism: a random discrete backoff time is selected from a predefined first-attempt CW value, i.e., the minimum contention window $\mathrm{CW}_{\text {min }}$. The backoff time counts backward but is frozen once the channel is occupied by other vehicle transmissions; the backoff time resumes until the channel is idle for another DIFS. Once the backoff time of one vehicle is first reduced to 0 after DIFS, the vehicle packets are transmitted at the first transmission attempt. If a transmission attempt fails, CW will be doubled until reaching the maximum allowed contention window $\mathrm{CW}_{\text {max }}$.

## IV. Formulation of Interdependent Mobility Model

In this section, we first introduce the mobility model. To solve the formulated mobility model, the mobility model is further shown in the rescaling space, and the average velocity and density distributions are discussed.

## A. Interdependent Mobility Model

Consider that the dynamics of a group of vehicles that are within the coverage of an AP. Let $N$ denote the number of vehicles. All vehicles move along a straight line on a highway, with no lane changing. The movement of vehicles can be described by generalized Langevin dynamics [13], [14]. Let $X_{i}(t)$ and $V_{i}(t)$ denote the position and velocity of the $i$ th vehicle $i=1, \ldots, N$ in time period $t$. Based on stochastic Newtonian equations, with an infinitesimally small time duration $d t>0$, we have

$$
\begin{align*}
d X_{i}(t) & =V_{i}(t) \cdot d t  \tag{1}\\
d V_{i}(t) & =\left(A_{i}(t)+\sum_{j \neq i} A_{i j}(t)\right) \cdot d t+B_{i}(o, d t) . \tag{2}
\end{align*}
$$

Here, according to [13], $A_{i}(t)$ and $A_{i j}(t)$ denote the deterministic accelerations of the $i$ th vehicle in time period $t$, introduced by itself and by others (e.g., vehicle $j$ ), respectively. $A_{i j}(t)$ describes relative movements of neighboring vehicles in time period $t . B_{i}(o, d t)$ denotes stochastic perturbations due to individual driver behaviors and $o$ is defined as an infinitesimally small change of positions.

Equations (1) and (2) formulate a mobility model which captures the dynamic vehicle-density and mobility dependency. Note that this mobility model is from each vehicle's perspective, thus is a microscopic model. We explain the variables $A_{i}(t), A_{i j}(t)$, and $B_{i}(o, d t)$ as follows.

1) Self-Acceleration $A_{i}(t)$ : Since each individual vehicle tends to adjust its speed to a preferred velocity $v^{*} \in \mathbb{R}$, the self-acceleration $A_{i}(t)$ in (2) is defined as [13]

$$
\begin{equation*}
A_{i}(t)=\gamma \cdot\left(v^{*}-V_{i}(t)\right) \tag{3}
\end{equation*}
$$

where $\gamma$ is a positive adjustment rate. Here, for simplicity, we suppose that all vehicles are the same with respect to a preferred velocity and adjustment rate.
2) Dependent Acceleration $A_{i j}(t)$ : The other acceleration term $A_{i j}(t)$ is applied by the $j$ th vehicle (i.e., the neighboring vehicle in front) onto the $i$ th one, due to a virtual interaction force. According to [13], we choose a simple quasi-linear dependence

$$
\begin{equation*}
A_{i j}(t)=\frac{1}{\left|R_{i j}(t)\right|}\left\{\alpha\left(\left|R_{i j}(t)\right|\right) R_{i j}(t)+\mu\left(\left|R_{i j}(t)\right|\right) H_{i j}(t)\right\} \tag{4}
\end{equation*}
$$

where position difference $R_{i j}(t)$ (i.e., headway distance) is denoted by $R_{i j}(t)=X_{j}(t)-X_{i}(t) \neq 0$ in time period $t$, and velocity difference as $H_{i j}(t)=V_{j}(t)-V_{i}(t)=\frac{d}{d t} R_{i j}(t)$. Consider that both quantities $R_{i j}(t)$ and $H_{i j}(t)$ can be measured by the visual sensing and communication system of
moving vehicles, e.g., the deployed loop detectors or multiple cameras. The function $\alpha(\cdot)$ depends on headway distance and represents the effect of a headway distance on $A_{i j}(t) ; \mu(\cdot)$ is also a function depending on a headway distance while representing the effect of velocity difference on $A_{i j}(t)$. Note that we only consider the nearest neighboring vehicle in front which impacts on the dependent acceleration.
3) Gaussian Noise: For vehicle $i$, the independent stochastic noise term $B_{i}(o, d t)$ in (2) is modeled with the mean neighbor distance $\delta$. Under $\delta \rightarrow 0$, as in [13]

$$
\begin{equation*}
B_{i}^{\delta}(o, d t)=\frac{b}{\sqrt{\delta}} W_{i}(d t) \tag{5}
\end{equation*}
$$

where the mutually independent Wiener increment $d W_{i}=$ $W_{i}(d t)$ represents the leading term of stochastic noise, as Gaussian white noise with a variance $b^{2} / \delta \cdot d t . b$ is a constant noise amplitude.

## B. Mobility Model in Rescaling Space

Consider a proper and reasonable rescaling procedure: only the vehicle $j=i+1$ is perceived by $i$ th vehicle, i.e., only the nearest-neighbor interaction is considered in this paper. On the same lane, in the moving direction, $N$ vehicles on a road within the courage range of the AP do not collide with each other, i.e., the positions $X_{i}(t)$ do not overlap, with an ordered chain: $X_{1}(t)<X_{2}(t)<\cdots<X_{N}(t)$.

Let $L(t)$ denote the road length with the same as the vehicle group length at time $t L(t):=X_{N}(t)-X_{1}(t)$. If $N$ goes to $\infty$ for a large group number in a dense network, this group length stays bounded by the coverage range of the AP. Then, $\delta:=\frac{L}{N}-L_{0}$, approximating the mean distance between neighbors within the group, where $L_{0}$ is the length of a vehicle; the average neighboring distance becomes infinitesimally small, i.e., $\delta \rightarrow 0$.

If the time scale keeps constant, the distance scales as $\delta$, i.e., $R_{i j}(t) \sim \delta$, so does a velocity difference $\frac{d}{d t} R_{i j}(t) \sim \delta$. Thus, as in [13], we define relative distances and relative velocity differences as follows.

1) With $R_{i}(t):=X_{i+1}(t)-X_{i}(t) \sim \delta$, we define the relative neighboring vehicle distances as $r_{i}(t)=\frac{R_{i}(t)}{\delta}$.
2) With $W_{i}(t):=V_{i+1}(t)-V_{i}(t) \sim \delta$, we define the relative vehicle velocity difference as $w_{i}(t)=\frac{W_{i}(t)}{\delta}$.
Finally, the rescaled parameter functions are

$$
\begin{align*}
\alpha\left(R_{i}(t)\right) & =\frac{1}{\delta} F\left(r_{i}(t)\right)  \tag{6}\\
\mu\left(R_{i}(t)\right) & =\frac{1}{\delta} M\left(r_{i}(t)\right) \tag{7}
\end{align*}
$$

where $F\left(r_{i}(t)\right)$ is the rescaled attraction-repulsion force or tension function; $M\left(r_{i}(t)\right)$ is the relative velocity adjustment coefficient function as in [13]. Note that both functions depend only on the rescaled distance variable $r_{i}(t)$ of vehicle $i$.

Rearranging (4), in the case of the nearest-neighboring vehicle interaction, we have

$$
\begin{equation*}
A_{i(i+1)}(t)=\frac{1}{\delta} \cdot \Im\left(\frac{R_{i}(t)}{\delta}, \frac{W_{i}(t)}{\delta}\right), \quad \text { for } i=1, \ldots, N-1 \tag{8}
\end{equation*}
$$

where the rescaled force or tension between two neighboring vehicles is defined as [13]

$$
\begin{align*}
\Im\left(\frac{R_{i}(t)}{\delta}, \frac{W_{i}(t)}{\delta}\right)= & F\left(r_{i}(t)\right)+M\left(r_{i}(t)\right) \cdot \frac{w_{i}(t)}{r_{i}(t)} \\
& \text { for } r_{i}(t)>0 \text { and } w_{i}(t) \in \mathbb{R} . \tag{9}
\end{align*}
$$

Therefore, the generalized Langevin dynamic for a group vehicles only with the nearest neighbor interaction is as

$$
\begin{align*}
d X_{i}(t)= & V_{i}(t) \cdot d t  \tag{10}\\
d V_{i}(t)= & \gamma \cdot\left(v^{*}-V_{i}(t)\right) \cdot d t+\frac{1}{\delta}\left\{\Im\left(r_{i}(t), w_{i}(t)\right)\right\} \cdot d t \\
& +B_{i}^{\delta}(o, d t) \tag{11}
\end{align*}
$$

where $r_{i}(t)=\frac{X_{i+1}(t)-X_{i}(t)}{\delta}$ and $w_{i}(t)=\frac{V_{i+1}(t)-V_{i}(t)}{\delta}, i=$ $1, \ldots, N-1$, are the rescaled distances and velocity differences between nearest neighboring vehicles.

Thus, (10) and (11) are equal to a generalized Langevin system of $2 \cdot N$ stochastic ordinary differential equations; to solve these model equations, both the vehicles' velocities and neighbor distances can be obtained. Note that vehicle densities is inversely proportional to the neighbor distances.

## C. Average Velocity and Density Distributions

As in [13], let $\overline{X(t)}$ and $\overline{V(t)}$ denote the average location and mean velocity of $N$ vehicles, respectively. They can be calculated by

$$
\begin{align*}
d \overline{X(t)} & =\frac{1}{N} \sum_{i=1}^{N} \overline{X_{i}(t)}  \tag{12}\\
d \overline{V(t)} & =\frac{1}{N} \sum_{i=1}^{N} \overline{V_{i}(t)} \tag{13}
\end{align*}
$$

The average location $\overline{X(t)}$ in time period $t$ represents the center of the vehicle group.

From (10)-(13), we have

$$
\begin{align*}
d \overline{X(t)}= & \overline{V(t)} d t  \tag{14}\\
d \overline{V(t)}= & \gamma \cdot\left(v^{*}-\overline{V(t)}\right) \cdot d t \\
& +\left(\frac{2 \eta}{N}\right) \sum_{i=1}^{N-1}\left\{\Im\left(r_{i}(t), w_{i}(t)\right)\right\} \cdot d t \\
& +\frac{1}{N} \sum_{i=1}^{N-1} B_{i}^{\delta}(o, d t) \tag{15}
\end{align*}
$$

where $\eta$ represents the impact factor by the neighbor vehicles. Under the condition $N \rightarrow \infty, \delta \rightarrow 0$. Given a finite space, the average vehicle distance converges to zero. Namely, $\delta=\frac{L}{N} \rightarrow$ 0 . Under this continuum limit condition, we define a density function $u(\cdot)$ as [13]

$$
\begin{equation*}
u(x, t)=\frac{1}{r(x, t)} \equiv \frac{\delta}{R_{i}(t)} \tag{16}
\end{equation*}
$$

Next, we redefine static parameter functions as functions of density $u>0$. Let $f(u)$ and $\mu(u)$ denote the static pressure and viscosity factor as [13],

$$
\begin{align*}
& f(u)=F\left(\frac{1}{u}\right)  \tag{17}\\
& \mu(u)=M\left(\frac{1}{u}\right) \tag{18}
\end{align*}
$$

Thus, the local tension can be written as

$$
\begin{equation*}
\Im=F(r)+M(r) \cdot \frac{w}{r}=f(u)+\mu(u) \cdot \partial_{x} v \tag{19}
\end{equation*}
$$

Based on (17)-(19), (14) and (15) can be represented as in generalized Navier-Stokes equations [13]

$$
\begin{align*}
\partial_{t} u+\partial_{x}(u v)= & 0  \tag{20}\\
\partial_{t} v+v \cdot \partial_{x} v= & \gamma \cdot\left(v^{*}-v\right)+\frac{1}{u} \cdot \partial_{x} f(u)+\mu(u) \cdot \partial_{x} v \\
& +2 \eta\left\{f(u)+\mu(u) \cdot \gamma_{x} v\right\} \tag{21}
\end{align*}
$$

Based on the results from [12], the pressure function $f(u)$ can be represented as

$$
\begin{equation*}
f(u)=-c_{o}^{2} u \tag{22}
\end{equation*}
$$

where $c_{o}$ is the standard deviation of the vehicular speed distribution, and the viscosity function $\mu(u)$

$$
\begin{equation*}
\mu(u)=\mu_{o} \tag{23}
\end{equation*}
$$

The pressure function $f(u)$ is proportional to the variance of vehicular speed and density. The viscosity function is a constant.

Solving (20) and (21), the vehicle-density of any position at any time period can be predicted based on current information.

## V. Vehicle-Density-Oriented MAC Protocol

Based on the mobility model proposed in the previous section, we present an algorithm to predict an adaptive CW size, which is calculated by the traffic server according to the current information (i.e., vehicle-densities and velocities), and be delivered and applied by an AP via the Internet connections.

## A. Dynamic Vehicle-Density-Oriented DCF

We design a vehicle-density-oriented DCF to exploit the dynamic vehicle-density for V2I/I2V communications, i.e., how to determine a V2I CW size $W$ for vehicles based on the collected information of vehicle locations and velocities. Note that $W$ represents the initial minimum CW size, $\mathrm{CW}_{\min }$ as in Section III-B; $u(x, t)$ is the vehicle-density distribution at location $x$ in time period $t$ as in Section IV-C. Let $U(t)$ denote the accumulate number of vehicles in a transmission range $r$ of an AP at location $x_{0}$ in time period $t$. Given the vehicle-density is predicted as $u(x, t)$, we have

$$
\begin{equation*}
U(t)=\int_{x_{0}-r}^{x_{0}+r} u(x, t) d x \tag{24}
\end{equation*}
$$

For each vehicle, a V2I transmission probability in time period $t$ is $p_{t}$. Then, when there are $U(t)$ vehicles in time period $t$, the collision probability $p_{t}^{f}$ is

$$
\begin{equation*}
p_{t}^{f}=1-\left(1-p_{t}\right)^{U(t)-1} \tag{25}
\end{equation*}
$$

which is the probability that there are more than one V2I transmission attempt within the same slot time.

Based on a DCF CA mechanism shown in Section III-B, if $\mathrm{CW}_{t}^{\mathrm{min}}$ is set as the CW size $W_{t}$ in time period $t$, for the first attempt, a backoff time is uniformly chosen from [0, $W_{t}$ ] for individuals. If the first attempt fails, a backoff time is further uniformly chosen in $\left[0,2 W_{t}\right]$ for individuals for the second attempt. Upon $k$ unsuccessful continuous attempts, the CW size $W_{k, t}$ is updated by $2^{k} W_{t}$ until the CW size reaches a maximum value $\mathrm{CW}_{t}^{\max }=2^{s} W_{t} ; k(k=0,1, \ldots, s)$ is denoted as the backoff stage $S$ [24]. Thus, given a successful transmission, the average CW size $\overline{W_{t}}$ for the first successful transmit is

$$
\begin{align*}
\overline{W_{t}} & =\sum_{k=0}^{s} W_{k, t} \cdot P(S=k \mid \text { successful transmit }) \\
& =\sum_{k=0}^{s} 2^{k} W_{t} \cdot \frac{\left(p_{t}^{f}\right)^{k}\left(1-p_{t}^{f}\right)}{1-\left(p_{t}^{f}\right)^{s+1}} \tag{26}
\end{align*}
$$

In an average sense, since the backoff time for time period $t$ is uniformly chosen from the CW size $\left[0, \overline{W_{t}}\right]$, the average backoff time for a successful transmit is $\frac{\overline{W_{t}}+1}{2}$. That is, on average, a vehicle waits for $\frac{\overline{W_{t}}+1}{2}$ time to successfully transmit messages to an AP. In other words, in a slot time, the successful transmission probability is $\frac{2}{\overline{W_{t}+1}}$. This successful transmission probability should be equal to $p_{t}$ to optimize the channel utilization level as discussed in [25], i.e.,

$$
\begin{equation*}
\overline{W_{t}}=\frac{2}{p_{t}}-1 \tag{27}
\end{equation*}
$$

Based on (25)-(27), we have

$$
\begin{align*}
& W_{t}=\frac{2-p_{t}}{p_{t}} \cdot \frac{2\left(1-p_{t}\right)^{U(t)-1}-1}{1-2^{s+1} \cdot\left[1-\left(1-p_{t}\right)^{U(t)-1}\right]^{s+1}} \\
& \cdot \frac{1-\left[1-\left(1-p_{t}\right)^{U(t)-1}\right]^{s+1}}{\left(1-p_{t}\right)^{U(t)-1}} \tag{28}
\end{align*}
$$

This implies that given a maximal backoff stage $s$ and the transmission probability $p_{t}$ for each vehicle in time period $t$, the initial CW size $W_{t}$ should be chosen with the variable of vehicle number $U(t)$ (representing vehicle-density) according to (28), to guarantee a successful transmission within the maximal backoff stage approaching the maximal channel utilization [25]. Therefore, based on (28), a vehicle-density-oriented MAC protocol is proposed as follows.

## B. Vehicle-Density-Adaptive MAC Protocol

Initially, a CW size starts with an arbitrary value within a predefined range. Once the information of both velocities and
headway distances collected from vehicles is received by the traffic server via the loop detectors/camaras, the traffic server starts to calculate and predict the number of vehicles around any AP's locale and analyze the predicted vehicle-density. Based on the received vehicle-density of a certain time period and location, the traffic server is able to predict the density pattern with the aforementioned mobility model (10) and (11) for any location in any time period. In order to mitigate the adverse effects of dynamic density and to increase the throughput in case of V2I transmission, the traffic server calculates a CW size through (28) based on the predicted dynamic vehicledensity and forwards the calculated CW size to the AP. Then, the vehicle-density-adaptive CW size is adapted by the AP to assign to individual vehicles.

The CW size adaptation is performed in response to network conditions, which are estimated by analyzing the received current vehicle velocities and locations, at MAC layer as discussed in Section V-A; dynamic adaptation of CW size causes changes in the backoff counter, so that timely transmission of messages occurs according to the perceived collision rate. That is, the vehicle-density-adaptive CW size is an indication of how information flow from a vehicle should be controlled to transmit according to the estimated collision rate. The main advantage of our proposed DCF is salient: it is fully adaptive to the vehicle-density changes or traffic flow fluctuation, which is particularly shown in vehicular communications as a notable feature. As this vehicle-density changes results in frequent collision-probability changes, the density-adaptive behavior of DCF makes the system quite robust and efficient.

## C. Throughput Analysis

By adapting vehicle-density-based distributed DCF in uploading scenarios, the adaptive MAC with taking the node mobility into consideration becomes applicable to the drivethru Internet networks. Based on the methodology in [26] and [27], a normalized throughput performance $\lambda$ is defined as the fraction of time of the channel utilized to successfully transmit payload bits; the system throughput $\lambda^{\text {total }}$ can be further obtained, representing the integrated throughput of all vehicles within an AP. Then, the nodal throughput $\lambda$ is denoted as the transmission rate of packet payloads by a vehicle in each transmission

$$
\begin{equation*}
\lambda=\frac{E[\text { payload transmitted in a slot time }]}{E[\text { length of a slot time }]}=\frac{E(P)}{E(T)} \tag{29}
\end{equation*}
$$

where $E(P)$ is the average packet payload successfully transmitted in a slot time and $E(T)$ is the average length of a slot time.

1) Average Transmitted Payload Size $E\left(P_{t}\right)$ for Time Period $t$ : Consider $U(t)$ vehicles in time period $t$ on the channel, and each vehicles with probability $p_{t}$ to transmit. Let $P_{t}^{\mathrm{tr}}$ be the probability that there is at least one transmission in the slot time, i.e.,

$$
\begin{equation*}
P_{t}^{\operatorname{tr}}=1-\left(1-p_{t}\right)^{U(t)} \tag{30}
\end{equation*}
$$

For each successful transmission, there should be only one transmission for the CA, conditioned on the fact of at least one
transmission. The conditional probability $P_{t}^{s}$, when exactly one vehicle in on the channel, is

$$
\begin{equation*}
P_{t}^{s}=\frac{C_{U(t)}^{1} p_{t}\left(1-p_{t}\right)^{U(t)-1}}{P_{t}^{\operatorname{tr}}}=\frac{U(t) p_{t}\left(1-p_{t}\right)^{U(t)-1}}{1-\left(1-p_{t}\right)^{U(t)}} \tag{31}
\end{equation*}
$$

In this case, all packets have the same fixed size $L$. Then, the average amount of payload information successfully transmitted in a slot time is $P_{t}^{\mathrm{tr}} P_{t}^{s} L$, since a successful transmission occurs in a slot time with probability $P_{t}^{\operatorname{tr}} P_{t}^{s}$, i.e.,

$$
\begin{equation*}
E\left(P_{t}\right)=P_{t}^{\operatorname{tr}} P_{t}^{s} L \tag{32}
\end{equation*}
$$

2) Average Length of a Transmission Slot Time $E\left(T_{t}\right)$ in Time Period t: The average length of a slot time is considered in three cases, which are: 1) the slot time is empty when there is no vehicle to transmit, with the probability $\left(1-P_{t}^{\mathrm{tr}}\right)$; 2) a transmission is successful in a slot time when there is only one vehicle to transmit, with the probability $P_{t}^{\operatorname{tr}} P_{t}^{s}$; and 3) a collision happens in a slot time when there are more than one vehicle to transmit, with the probability $P_{t}^{\operatorname{tr}}\left(1-P_{t}^{s}\right)$.

Furthermore, based on [26], the length of a slot time under the above three cases are, respectively, as follows: 1) the duration of an empty slot time $\sigma ; 2$ ) the length of a slot time for a successful transmission in the basic access mechanism $T^{s}=H+L+\mathrm{SIFS}+\delta+\mathrm{ACK}+\mathrm{DIFS}+\delta$, where $H=\mathrm{PHY}_{\mathrm{hdr}}+M A C_{\mathrm{hdr}}$ is the packet header and $\delta$ is the propagation delay; and 3) the duration of a collision slot time $T^{c}=H+L+$ DIFS $+\delta$. Therefore, the average length of a slot time is

$$
\begin{equation*}
E\left(T_{t}\right)=\left(1-P_{t}^{\operatorname{tr}}\right) \sigma+P_{t}^{\operatorname{tr}} P_{t}^{s} T^{s}+P_{t}^{\operatorname{tr}}\left(1-P_{t}^{s}\right) T^{c} \tag{33}
\end{equation*}
$$

Therefore, combining (29)-(33), we get (34), shown at the bottom of the page.

If all the packets of vehicles have the same length, the system throughput of the AP $\lambda_{t}^{\text {total }}$ is

$$
\begin{equation*}
\lambda_{t}^{\text {total }}=U(t) \lambda_{t} \tag{35}
\end{equation*}
$$

Note that (34) implies that given a transmission probability $p_{t}$ for each vehicle and the packet length $L$, the nodal throughput $\lambda_{t}$ should be decided by the variable of vehicle number $U(t)$ (representing vehicle-density) according to (28). Therefore, based on (34) and (35), the nodal throughput and system throughput can be, respectively, calculated approaching the maximal channel utilization.

## VI. Performance Evaluation

In this section, we first simulate a realistic vehicular scenario in VISSIM, ${ }^{3}$ as shown in Fig. 3, to illustrate the fluctuating

[^3]

Fig. 3. Snapshot of the simulation region on a highway in VISSIM.
vehicle-density. Then, we present the numerical results of the fluctuating vehicle-density and velocity achieved from the utilized mobility model in Section IV in the same highway scenario. Since the communication performances cannot be evaluated by the external algorithm in VISSIM, we further develop a MATLAB-based platform to investigate the performances of our proposed MAC design, which is adaptive to the fluctuating vehicle-density based on the vehicular traces.

## A. Vehicle-Density Illustration in VISSIM

To simulate a drive-thru Internet in VISSIM, a highway is drawn as long as 10000 m , with three lanes in a moving direction, as shown in Fig. 3. During the simulation, vehicles are pushed into the highway from the presented entries (e.g., three entries at the ends of the lanes of the highway), following a Poisson process at a certain rate, e.g., 4320 vehicle/h/entry. The initial velocities of vehicles are chosen uniformly within ( $80 \mathrm{~km} / \mathrm{h}, 120 \mathrm{~km} / \mathrm{h}$ ), and the safe distance between vehicles is set to be 40 m . The simulation time is 4000 s . In addition, APs with a transmission radius 300 m are deployed one by one, along the highway to fully cover the highway.
The simulated vehicle-density is shown in Fig. 4, under two settings. One setting in Fig. 4(a) is with only one intersection (i.e., one highway exit) along the highway; the other in Fig. 4(b) is with three intersections (e.g., highway exits). We can see that the vehicle-density is fluctuating with both time and position, and the density peak is spreading afterward with position like waves.

## B. Numerical Results of the Utilized Mobility Model

Based on the discussed mobility model, we can formulate and illustrate the fluctuating vehicle-density under two settings, e.g., with one intersection and three intersections along the considered highway. Fig. 5 shows how the vehicle-density changes with time and position based on the applied mobility model. We can observe that the vehicle-density is dynamically fluctuating in a range of ( 20 vehicle/km, 40 vehicle/km). As shown in Fig. 5, the vehicle-density fluctuation under our mobility model is capable of illustrating the fluctuation trends obtained through VISSIM in Fig. 4. First, as shown in Fig. 5(a) and (b), the peak vehicle-density is located at the intersections. This is due to the reduced velocities of vehicles to make turnings at the intersections. As time goes, the peak of the vehicle-density

$$
\begin{equation*}
\lambda_{t}=\frac{P_{t}^{\operatorname{tr}} P_{t}^{s} L}{\left(1-P_{t}^{\mathrm{tr}}\right) \sigma+P_{t}^{\mathrm{tr}} P_{t}^{s} T^{s}+P_{t}^{\mathrm{tr}}\left(1-P_{t}^{s}\right) T^{c}}=\frac{U(t) p_{t}\left(1-p_{t}\right)^{U(t)-1} L}{\left(1-p_{t}\right)^{U(t)} \sigma+U(t) p_{t}\left(1-p_{t}\right)^{U(t)-1} T^{s}+\left[1-\left(1-p_{t}\right)^{U(t)}-U(t) p_{t}\left(1-p_{t}\right)^{U(t)-1}\right] T^{c}} \tag{34}
\end{equation*}
$$



Fig. 4. Dynamically fluctuating vehicle-density in VISSIM. (a) The first setting with one intersection on the highway. (b) The second setting with three intersections on the highway.
moves backward. This phenomena can be seen from real life and is reasonable: when the vehicle-density is high ahead, vehicles tend to lower the speed, leading to a higher density at their current location, and thus the location of the peak moves backward; and when the vehicle-density ahead is low, vehicles tend to speed up, leading to a decreased vehicle-density at the location

Fig. 6 illustrates the dynamically fluctuating vehicle-velocity, accordingly. It is shown that when the vehicle-density is high (e.g., 40 vehicles $/ \mathrm{km}$ ), the vehicle-velocity is low (e.g., $12 \mathrm{~m} / \mathrm{s}$ ); whereas, lower vehicle-density (e.g., 20 vehicles $/ \mathrm{km}$ ) is with the average speed of $28 \mathrm{~m} / \mathrm{s}$. This is because with a small average headway distance due to the increased vehicle-density, vehicles adjusts to a lower speed in our mobility model. In comparison, when the vehicle-density decreases, vehicle-velocity becomes higher, accordingly.

## C. Simulation Results of the Designed MAC

In the following, taking the case with three intersections as an example, based on the analysis in Section V-A, the CW


Fig. 5. Dynamically fluctuating vehicle-density based on the utilized mobility model. (a) The first setting with one intersection on the highway. (b) The second case with three intersections on the highway.
size should be adaptive to the dynamically fluctuating vehicledensity according to (28). The transmission probability is set as 0.02 . Fig. 7 illustrates that how the CW size $W$ changes with the density of vehicles based on (28). Generally, with a higher vehicle-density, the CW size is chosen to be larger than the low-vehicle-density case.

To evaluate the effectiveness of our proposed MAC protocol, we compare the system throughput of each AP under our proposed MAC protocol to the throughput performance with the traditional MAC protocol [4], in which the CW size is fixed to a constant. Since the vehicle-densities and velocities at the intersections perform the similar trends as shown in Figs. 5(b) and fig6(b), to make the figures more clear to illustrate the results, we only show the first 5000 m of the highway to illustrate the throughput performance. Figs. 8 and 9 show the throughput performance under the conventional MAC and our proposed MAC protocol, respectively. As we can see from Fig. 8, when the vehicle-density increases to its peak, the throughput drops dramatically. For example, the throughput performance drops dramatically nearby the location of an intersection with the high vehicle-density of 40 vehicles $/ \mathrm{km}$. This drop in throughput


Fig. 6. Dynamically fluctuating vehicle-velocity based on the mobility model. (a) The setting with one intersection on the highway. (b) The setting with three intersections on the highway.


Fig. 7. CW size setting based on the proposed MAC.
is reasonable, since with the increased number of vehicles, the collisions among transmissions increase, resulting in lower throughput. However, with the adaptive CW size according to


Fig. 8. Throughput performance based on the conventional MAC.


Fig. 9. Throughput performance based on the proposed MAC.


Fig. 10. Increment of throughput via the proposed adaptive MAC.
our proposed MAC protocol, as shown in Fig. 9, a more smooth and higher throughput performance (e.g., around $3.86 \mathrm{Mb} / \mathrm{s}$ ) can be achieved, compared to the conventional MAC (e.g., $3.4 \mathrm{Mb} / \mathrm{s})$. The reason is that, our proposed MAC increases


Fig. 11. Throughput gain via the proposed adaptive MAC.
the CW adaptively when the vehicle-density increases, thus reducing the number of transmission collisions.

Figs. 10 and 11 show the throughput performance gain of our proposed vehicle-density-adaptive MAC protocol, compared to the throughput performance based on a fixed CW size. As we can see from Figs. 10 and 11, the proposed MAC protocol can always obtain a larger throughput performance compared to the conventional MAC protocol, and the performance gain increases with the increase in the vehicle-density. Specifically, the performance gain is about $0.2 \mathrm{Mb} / \mathrm{s}$, namely $6 \%$, under low vehicle-density scenario, and increases to about $0.45 \mathrm{Mb} / \mathrm{s}$, namely $13 \%$, under high vehicle-density scenario. This result suggests that our proposed MAC protocol is suitable for the drive-thru Internet application in VANET with dynamic vehicle-density.

## VII. Conclusion

In this paper, we have proposed a vehicle-density-aware MAC protocol for high throughput in drive-thru Internet, based on the prediction of vehicle-density dynamics. First, we utilize Navier-Stokes equations to model the mobility of vehicles for the prediction of the dynamically waving vehicle-density. Based on the predicted dynamic vehicle-density, we propose an enhanced MAC protocol to adaptively adjust the CW setting to improve the throughput. The extensive simulations demonstrate the effectiveness of the proposed MAC protocol in throughout improvement. For the future work, we will study the impact of the dynamic vehicle-density on other network performance such as average interaction duration among vehicles. Moreover, how to leverage both the dynamic vehicle-density and cooperation among vehicles and/or APs (e.g., [28] and [29]) to further improve throughput performance will be investigated.

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[^1]:    ${ }^{1}$ In biology, the dynamic phenomena of queueing skeins of migrating birds are fairly reproduced by stochastic ordinary differential equations for a multiparticle system including the individual tendency of birds to attain a preferred speed as well as mutual interaction forces between neighbors, induced by distance dependent attraction/repulsion (i.e., virtual forces) and adjustment of velocities [13], [14].

[^2]:    ${ }^{2}$ Since the other direction can be considered similar to this scenario, we focus on only one moving direction in this work. However, the study can be applied for both directions on the highway.

[^3]:    ${ }^{3}$ PTV VISSIM is the commercial software dedicated for traffic modeling based on vehicle real traces. It is a powerful vehicle mobility simulator widely adopted in civil engineering, which implements the adopted models on intersection policies, speed limitations, and safety distances between vehicles, etc, and provides high-fidelity simulations on vehicle mobility.

