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MAC Performance Analysis for Drive-Thru Internet Networks With Rayleigh Capture

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ABSTRACT In practical radio transmissions, channel capture is a dominating factor that affects wireless network performance. The capture effect can occur in wireless network when packets arrive with different powers. Packets with high power can effectively swamp low power packets, such that they are received successfully, when otherwise a collision would have occurred. We present a vehicular network performance-prediction model for a Rayleigh capture channel in Drive-thru Internet scenario. The model incorporates the capture effect into a 2-D Markov chain modeling the high-node mobility and distributed coordination function broadcast scheme. The performance-prediction model unveils the impacts of mobility velocity and number of vehicles on the throughput in a Rayleigh capture channel. We use a vehicular traffic flow model to predict vehicular movement on road by aggregating all vehicles into a flow. Simulation results confirm that our performance-prediction model accurately predicts the performance of traveling vehicles with Rayleigh capture channel in the Drive-thru Internet scenario. We demonstrate that using our performance-prediction model, we can obtain optimal contention window value, by which the best system throughput can be reached without wasting contention time. This is also proved by Anastasi *et al.*

INDEX TERMS Capture effect, performance analysis, Markov chain, DCF, Drive-thru Internet, VANETs.

I. INTRODUCTION

With the advent of various mobile Internet applications and social network services (e.g., watching videos, browsing daily news, talking with friends on Skype and video conferencing), our life nowadays is more caught in a variety of multimedia services than ever before. In addition, due to increased motorization and urbanization, people spend more time in vehicles. Consequently, more people intend to access the media-rich contents on the Internet from moving vehicles. Moreover, to reduce traffic accidents, traffic congestion, transportation time and carbon emissions, Intelligent Transport Systems (ITS) services have recently been more and more demanded. As a result, Internet connectivity to vehicles has become an indispensable part of our road lives towards enhanced safety, efficiency and comfort.

Although people can use cellular networks (e.g., GPRS, 3G and 4G) or satellite networks to access the Internet in moving vehicles, these access technologies suffer from low rate, high cost, long latency, and the capacity of the cellular networks is close to the limits [2]. In order to cater to the ever-increasing demand, the Drive-thru Internet has recently been introduced, which provides the high rate yet cheap Internet access to traveling vehicles along the roads by utilizing the IEEE 802.11 access points (APs) [3].

Significant work has been done on analyzing Media Access Control (MAC) performance of vehicular Ad hoc networks (VANETs) [4]–[7]. However, they do not consider vehicular nodes movement in their analytical model. The real situation is that vehicles move fast on roads and topology changes frequently. So the MAC performance of the vehicular network is unknown. In order to address this problem, we proposed several simple yet accurate analytical models to evaluate the MAC performance in the vehicle-to-infrastructure (V2I) communications with fast moving vehicle nodes in previous work [3], [8]–[11]. While the above models characterise MAC of VANETs, an ideal transmission channel is assumed in all of them. When there is no collision, it is considered that a transmitted packet is successfully received and otherwise lost.

In fact, due to multipath, shadowing, and fading, the signals transmitted by a vehicle node arrive at the receiver with different power levels. When there is collision, the so-called ''capture effect'' may take place, such that the packet with highest power at the receiver can be successfully received [12]–[15]. Although these papers introduce capture effect, they do not consider highly mobile vehicular environment and also they do not model movement of vehicle nodes. Mobility in ad hoc networks was explored in [16], which added mobility to the model in [17]. They found that mobility dramatically increased the throughput in ad hoc networks when there are loose delay constraints. However, they assumed saturated nodes, did not model the Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) channel access mechanism, and used random walks for movement.

In this paper, we incorporate the capture model into a 2-dimensional (2-D) Markov chain model [8]. The 2-D Markov chain integrates the 802.11 MAC scheme and vehicular node mobility into one model to model IEEE 802.11 Distributed Coordination Function (DCF) in the fast moving vehicular environment. We can evaluate the DCF performance of V2I communications with fast moving vehicle nodes using the simple yet accurate analytical model. With the new 2-D model including capture effect, we can research the impacts of vehicular node mobility and the capture effect on important performance measures, such as collision probability and throughput, in the highly mobile vehicular environment with Rayleigh capture which are difficult to achieve with the above-mentioned models [4]–[7]. Extensive simulations demonstrate the accuracy of our new performance-prediction model.

The rest of paper is organised as follows: Related works are discussed in Section II. In Section III we briefly present IEEE 802.11 DCF in the context of VANETs. In Section IV we present a 2-D Markov chain performance-prediction model for analyzing the MAC performance of VANETs in a Rayleigh capture channel in detail. In Section V we validate the accuracy of the performance-prediction model and evaluate the MAC performance with numerical and simulation results. Concluding remarks are given in Section VI.

II. RELATED WORK

Significant work has been done on the design and analysis of VANETs. In [18], a 2-D Markov chain model is proposed by Bianchi to analyze the binary exponential backoff procedure of DCF under saturated conditions and present results in terms of bounds on achievable throughput. This model has since been extended to finite traffic load [19] and more practical conditions of finite packet retry limits [20]. In [21], Liu *et al.*. present a 3-dimensional (3-D) Markov chain model for systems with finite buffer under finite load. The model incorporates the 802.11 MAC scheme and queueing processes into one model. The third dimension is added to model the finite interface queue and accurately characterises the QoS performance of 802.11 networks. These models are classical models which analyse IEEE 802.11 MAC and much work has been done on work relevant to 802.11 MAC based on these classical models.

In [4], 1-D Markov model incorporating a discrete time D/M/1 queue is presented to analyse the broadcast performance of VANETs such as average packet delay and packet collision probability. An idle state is added to the model for modeling unsaturated traffic. However, note that infinite buffer size is assumed. There will be no packet blocking using the infinite buffer size. As such, accurate QoS parameters cannot be obtained by this 1-D model, such as queueing delay and blocking probability. In [5], a 2-D Markov chain queueing model is presented. The model incorporates the broadcast scheme of the 802.11 MAC and queueing processes into one model. The extra dimension, that models the queue length, accurately capture important QoS measures for realistic 802.11 broadcast systems with finite buffer under finite load. In [6], an analytic model combining a discrete time M/G/1 queue with a 1-D Markov model is presented to evaluate the broadcast performance of IEEE 802.11 networks such as packet delivery ratio, throughput, packet delay and service time distribution in safety related vehicle-to-vehicle (V2V) communication. The discrete time M/G/1 queue modeled occasional occurrences of safety related messages in each vehicle and the 1-D Markov chain modeled the backoff counter process of each station in IEEE 802.11 broadcast network. In [7], Zhang *et al.* propose a novel protocol called vehicular cooperative media access control (VC-MAC). VC-MAC uses cooperative relaying to overcome the unreliability of the wireless channel to improve the throughput.

To study the unclear performance of DCF in the fast moving vehicular environment, Luan *et al.* propose an accurate analytical model to investigate the DCF performance of the high-speed V2I communications in [8]. The model is saturated and 2-D in which the first dimension denotes the spatial zone which one vehicle node is currently associated with and the second dimension denotes its backoff counter at one time slot. In order to address the performance anomaly, they propose that vehicle nodes in different zones send packets with different probabilities and then model MAC scheme as the p-persistent CSMA. In [3], they design an analytical model which combines the fast mobility of vehicle nodes with 802.11 MAC scheme and unveil the impacts of mobility on the resultant throughput. Based on the model, they show that the throughput of DCF will be reduced with the increase of node velocity because of the mismatch between the transient high-throughput connectivity of vehicles and the MAC scheme. In [9], Li *et al.* investigate the MAC scheme of Drive-thru Internet in a sparse highway environment by a Markov chain encountering model. The analytical model combines the fast mobility of nodes with the DCF scheme and unveils the impacts of mobility velocity and number of vehicles on the throughput. Based on the model, we develop a new MAC scheme and show that when the number of vehicles is small

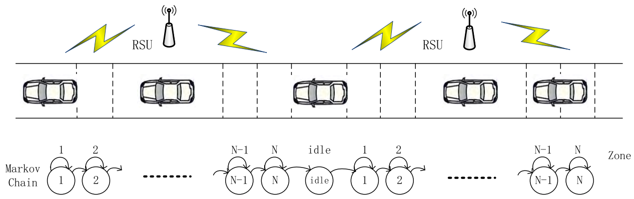

FIGURE 1. V2I encountering model along a straight.

the proposed MAC scheme can obtain higher throughput and mitigate the impacts of vehicle mobility on the system throughput, which is desirable for the sparse highway environment.

III. DCF IN THE VEHICULAR ENVIRONMENT

Consider a scenario where multiple vehicle nodes pass roadside units (RSUs) deployed along the road as depicted in Fig. 1. Using IEEE 802.11 DCF, each vehicle node follows the CSMA/CA principle to compete for channel for sending packets. Nodes may have different transmission rates due to diverse signal strength. For example, 802.11b has four rates (1, 2, 5.5 and 11 Mbps) under different signal-to-noise ratio (SNR) values. For different distances from an RSU, a vehicle node has roughly a bell-curve SNR [22] and thus varying data rate. Hence, with multi-rate transmissions, it is shown that using DCF the system throughput is bottlenecked to the minimum transmission rate, namely *performance abnormal* [23]. As such, the performance abnormal would throttle the system throughput.

To address the performance abnormal, we divide the coverage area of an RSU into several zones based on the distance to RSU. More details about zones can be found in IV.B. We propose that vehicle nodes in distinct zones send packets with different probabilities, as done in [8]. Instead of modeling IEEE 802.11 DCF directly, we model the MAC scheme as the p-persistent CSMA. In order to reduce the collision probability among transmissions from multiple nodes, rather than selecting the backoff interval uniformly within Contention Window (CW) and doubling the CW upon each unsuccessful transmission, each vehicle node in zone n selects a geometrically distributed number of backoff intervals x with parameter p_n following

$$Pr\{x = k\} = \frac{(1-p_n)^k p_n}{G}, \qquad k \in [0, W-1],\ n \in \mathbb{Z} \quad (1)$$

where $G = \sum_{i=0}^{W-1} (1-p_n)^i p_n$. W is constant and the same for all the zones.

In the following, we establish an analytical model to evaluate the MAC performance of the high-speed vehicular network with Rayleigh capture.

IV. SYSTEM MODEL AND ANALYSIS

In this section, we detail our analytical model for evaluating the MAC performance in the fast moving Drive-thru Internet with practical Rayleigh capture channels.

A. ASSUMPTION

First of all, we assume that all vehicles in VANETs are equipped with on-board-units (OBUs) (i.e., GPS receivers, transceiver, router and sensors), from which the states of a vehicle (e.g., location, speed, direction, and acceleration) can be easily obtained and sent to other vehicles. Secondly, we assume that each RSU has the same coverage area and are equally spaced.

B. SYSTEM DESCRIPTION

We consider the V2I communication scenario as shown in Fig. 1, where there are several vehicle nodes connecting to intermittent and serial RSUs along the road for communication in non-ideal channel conditions. We are mainly absorbed in the MAC layer under the assumption of practical Rayleigh capture channels, which model the heavily built-up urban environment, such as homes and hot spots, but also consider speeds up to 120 km/h. In this scenario, the SNR and modulation rates of vehicle nodes are mainly determined by their distance from the RSUs. The assumption showing the strong correlation between transmission rate and distance in vehicular network has been partially confirmed in field tests [22].

Similarly to [8], we divide the coverage area of an RSU into several zones $\mathbb{Z} = \{1, 2, \ldots, N\}$ and denote the zone outside the coverage area of two adjacent RSUs by *idle* as shown in Fig. 1, where $\mathbb{Z} \cup \{idle\} = \mathbb{A}$. In each spatial zone n, $n \in \mathbb{A}$, vehicle nodes have the different payload transmission rates, denoted by pt_n, according to their distance from the RSU; especially in zone *idle*, the payload transmission rate is 0 due to no signal coverage. Denote the length of zone n by r_n and r_0 is the zone length of zone *idle*. We assume the average velocity of vehicle nodes in all zones is the same and let the average velocity of vehicle nodes be v. Then the duration that a vehicle node stays in zone n is geometrically distributed with mean t_n, such that $t_n = r_n/v$. The movement of vehicle nodes in each zone is modeled as a Markov chain, as shown in Fig. 1, in which each state stands for one zone in $\mathbb{A}$. If a node leaves the current RSU and enters coverage area of the next RSU, it is regarded to move from state N back to state 1 in the Markov chain. Within the radio coverage of an RSU, zones in the two sections divided by the RSU is symmetric based on their distances from the RSU. We let zone n_{map} be the symmetric zone of zone n, keeping $n_{map} \geq n$, such that $n_{map} = N + 1 - n$. Therefore, the zone length, transmission rate and duration are equal in symmetric zones n and n_{map}. We assume that N is an odd number for simplicity here, but it is also applicable for even number N. The packet length L is assumed to be the same for all the vehicle nodes.

C. VEHICULAR TRAFFIC FLOW MODEL

In this section, we introduce a vehicular traffic flow model called "speed-flow-density diagrams" [24] to model vehicular movement on road by aggregating all vehicles into a flow. The model describes the interdependent relationships

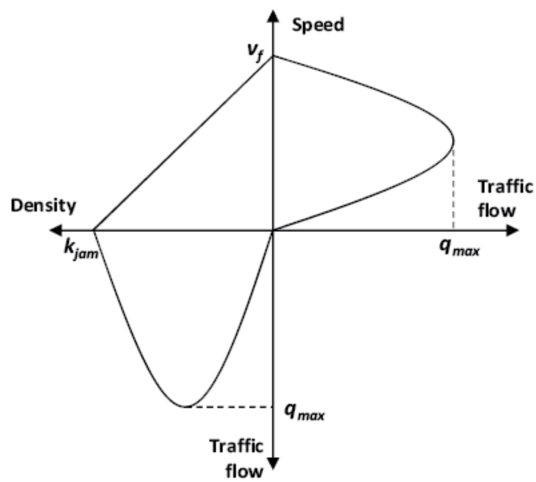

FIGURE 2. **Speed-flow-density diagram.**

between traffic flow, density and speed. The basic formula of traffic flow theory is expressed as follows:

$$q = k \times v, \tag{2}$$

where q represents the vehicle nodes flow (i.e., the arrival rate) measuring the number of vehicle nodes passing a fixed roadside observation point per unit time, k stands for the vehicle nodes density on roads and v is the vehicle node speed, where it is assumed that all vehicles travel at the same speed.

Greenshields developed the first linear expression with respect to the relationship between density k and speed v based on field observations [25]. The expression is as follows:

$$v = v_f \left(1 - \frac{k}{k_{jam}}\right), \tag{3}$$

where v_f is the free-flow speed (i.e., the maximum speed that vehicle nodes travel at and usually taken as the road's speed limit and we assume $v_f = 180$ km/h) and k_{jam} is the vehicle jam density at which traffic flow will be motionless and we assume $k_{jam} = 160$ cars per kilometer.

Combining equations (2) with (3), the typical speed-flow-density diagram can be constructed as depicted in Fig. 2. In the figure, the first quadrant describes the relationship between speed and traffic flow in which with speed increasing from zero, the traffic flow also increases parabolically from zero. As speed continues to increase, the traffic flow will reach a maximum value q_{max}. Beyond this point, if speed keeps increasing, traffic flow will decrease, and eventually reach zero when at maximum speed v_f. The second and third quadrants depict speed-density and flow-density relationships. As density increases, speed declines linearly and the traffic flow rises to the maximum value q_{max} first and then declines to zero as a parabola. Here we mainly focus on the speed-flow relationship. The relationship is as follows:

$$q = v \times \left(1 - \frac{v}{v_f}\right) \times k_{jam}, \tag{4}$$

D. MODELING CAPTURE EFFECT FOR NETWORK IN A NON-IDEAL CHANNEL

In the section, we focus on the capture effect coming from concurrent transmissions in the Drive-thru Internet. In real Rayleigh capture channel conditions, whether a transmission succeeds or not depends on the potential interference from concurrent transmissions. Here we adopt the definition signal to interference-plus-noise ratio (SINR) in [15], γ, to evaluate whether a transmitted packet is successfully received. The SINR can be expressed as follows:

$$\gamma = \frac{P_R^{(0)}}{P_N + \sum_{i=1}^{k} P_R^{(i)}}, \tag{5}$$

where $P_R^{(0)}$ denotes the power at the RSU of a particular transmission of interest; P_N is the power of background noise and $P_R^{(1)}, \ldots, P_R^{(k)}$, $k \in [1, z-1]$ are the powers at the RSU of k concurrent transmissions with the assumption that there are z vehicle nodes in the coverage area of the RSU($k \leq z$). When there is only one transmission from the node of interest (i.e. $k = 0$), the transmission signal only has the interference from the background noise, so the SINR reduces to the SNR. When there is more than one transmission (i.e. $k \geq 1$), the SINR includes both background noise and interfering signals. Let τ_n denote the conditional transmission probability, given a vehicle node is in zone n.

Let X denote the mean number of nodes in the road segment, and let q denote the mean arrival rate of nodes. According to Little's law

$$X = q \frac{\sum_{n \in \mathbb{A}} r_n}{v}, \tag{6}$$

where $\sum_{n \in \mathbb{A}} r_n$ is the length of the road segment and $\sum_{n \in \mathbb{A}} r_n / v$ is the mean sojourn time of nodes in the road segment. Let X_n denote the expected number of nodes in zone n, so that

$$X_n = \frac{q\, r_n}{v}, \tag{7}$$

Then the probability that there are k_n vehicle nodes having packets to transmit in zone n is as follows:

$$P_{k_n} = \binom{X_n}{k_n} {\tau_n}^{k_n} (1 - \tau_n)^{X_n - k_n}. \tag{8}$$

Here we consider three effects [12]: the attenuation due to the distance r, proportional to $r^{-\eta}$, where η, the power loss law exponent, assumes values between 2 and 4, and is typically taken equal to 4 in land mobile radio environments; the shadowing, described with a lognormal random variable; and the Rayleigh fading, which gives rise to the instantaneous envelope of the received signal to be Rayleigh distributed, and its power to be an exponentially distributed random variable. With these assumptions, the received power from a vehicle node at distance r can be expressed as

$$P_R = R^2 e^{\xi} K r^{-\eta} P_T, \tag{9}$$

where R is a Rayleigh distributed random variable with unit power; e^{ξ} accounts for the shadowing (ξ is Gaussian with zero mean and variance σ^2); $Kr^{-\eta}$ is the deterministic loss law, and P_T is transmitted power from vehicle nodes. K, η and P_T will be assumed to be the same for all vehicle nodes, whereas R and ξ will be assumed independent from vehicle to vehicle and identically distributed. For each zone n, $n \in \mathbb{Z}$, we assume all vehicle nodes in zone n are the same distance r_n from the RSU. So, for each zone n, the received power at the RSU from each vehicle node in the zone can be expressed as

$$P_{R,n} = R^2 e^{\xi} K r_n^{-\eta} P_T. \tag{10}$$

Similarly to [12], to compute the capture ratio, an outage is defined to have occurred in the event that the SINR falls below a predetermined threshold. Here we define h as the predetermined threshold and assume that a packet can be correctly received if its SINR γ is larger than the threshold h; otherwise it is incorrectly decoded. Based on aforementioned assumption, the probability that a packet from zone n is correctly received can be derived as follows:

$$p_{suc,n} = P[\gamma > h]_n, \tag{11}$$

where h is also a function of receiver sensitivity and we assume $h = 5$.

To obtain $p_{suc,n}$, we need to calculate the probability $p_{s,n}(\mathbf{k})$ that a packet is correctly received on condition that there are k_n transmitting vehicle nodes in each zone n, $n \in \mathbb{Z}$, where $\mathbf{k}$ is the vector $[k_1, \cdots, k_N]$ and $0 \leq k_n \leq X_n$. To focus on the multiple access, in what follows the effect of background noise will be neglected (i.e., $P_N = 0$). The probability $p_{s,n}(\mathbf{k})$ can be calculated as follows:

$$\begin{aligned}
&p_{s,n}(\mathbf{k}) \\
&= P[\gamma > h]_n \\
&= P\Bigg[\frac{R_0^2 e^{\xi_0} K r_n^{-\eta} P_T}{\sum_{i=1}^{k_1} P_{R,1} + \cdots + \sum_{i=1}^{k_n-1} P_{R,n} + \cdots + \sum_{i=1}^{k_N} P_{R,N}} > h\Bigg]_n \\
&= P\Bigg[\frac{R_0^2 e^{\xi_0} r_n^{-\eta}}{\sum_{z=1,z\neq n}^{N}\sum_{i=1}^{k_z} R_{z,i}^2 e^{\xi_{z,i}} r_z^{-\eta} + \sum_{i=1}^{k_n-1} R_{n,i}^2 e^{\xi_{n,i}} r_n^{-\eta}} > h\Bigg]_n \\
&= P\Bigg[R_0^2 > h\frac{\sum_{z=1,z\neq n}^{N}\sum_{i=1}^{k_z} R_{z,i}^2 e^{\xi_{z,i}} r_z^{-\eta} + \sum_{i=1}^{k_n-1} R_{n,i}^2 e^{\xi_{n,i}} r_n^{-\eta}}{e^{\xi_0} r_n^{-\eta}}\Bigg]_n \\
&= P\Bigg[R_0^2 > h\Bigg(\sum_{z=1,z\neq n}^{N}\sum_{i=1}^{k_z} R_{z,i}^2 e^{\xi_{z,i}-\xi_0}\Big(\frac{r_z}{r_n}\Big)^{-\eta} + \\
&\qquad \sum_{i=1}^{k_n-1} R_{n,i}^2 e^{\xi_{n,i}-\xi_0}\Bigg)\Bigg]_n
\end{aligned} \tag{12}$$

where only the dependence on r_n is explicitly indicated and $P_{R,n}$, $n \in \mathbb{Z}$ is the power of signal from zone n at the RSU.

When conditioned on all ξ, $p_{s,n}(\mathbf{k})$ can be computed as:

$$\begin{aligned}
&p_{s,n}(\mathbf{k}) \\
&= p[\gamma > h | k, \text{all } \xi]_n \\
&= \underbrace{\int_0^{\infty}\cdots\int_0^{\infty}} \exp\Bigg(-h\Bigg[\sum_{z=1,z\neq n}^{N}\sum_{i=1}^{k_z} e^{\xi_{z,i}-\xi_0}\Big(\frac{r_z}{r_n}\Big)^{-\eta} \\
&\quad + \sum_{i=1}^{k_n-1} e^{\xi_{n,i}-\xi_0}\Bigg]\Bigg) \prod_{z=1,z\neq n}^{N}\prod_{i=1}^{k_z}(e^{-x_{z,i}}dx_{z,i}) \\
&\quad \prod_{i=1}^{k_n-1}(e^{-x_{n,i}}dx_{n,i}) \\
&= \prod_{z=1,z\neq n}^{N}\prod_{i=1}^{k_z}\frac{1}{1+he^{\xi_{z,i}-\xi_0}(\frac{r_z}{r_n})^{-\eta}}\prod_{i=1}^{k_n-1}\frac{1}{1+he^{\xi_{n,i}-\xi_0}}
\end{aligned} \tag{13}$$

Then, if we want to remove the conditioning on ξ,

$$\begin{aligned}
&p_{s,n}(\mathbf{k}) \\
&= \underbrace{\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}}\int_{-\infty}^{\infty}\Bigg(\sum_{z=1,z\neq n}^{N}\sum_{i=1}^{k_z}\frac{f(x_{z,i})dx_{z,i}}{1+he^{x_{z,i}-x_0}(\frac{r_z}{r_n})^{-\eta}} \\
&\quad \times\prod_{i=1}^{k_n-1}\frac{f(x_{m,i})dx_{m,i}}{1+he^{x_{m,i}-x_0}}\Bigg)f(x_0)dx_0
\end{aligned} \tag{14}$$

where $f(x) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{x^2}{2\sigma^2}}$.

For the sake of simplicity, we do not consider shadowing effects (i.e., $\xi = 0$), giving:

$$\begin{aligned}
p_{s,n}(\mathbf{k}) &= \prod_{z=1,z\neq n}^{N}\prod_{i=1}^{k_z}\frac{1}{1+h(\frac{r_z}{r_n})^{-\eta}}\prod_{i=1}^{k_n-1}\frac{1}{1+h} \\
&= \Bigg(\prod_{z=1,z\neq n}^{N}\prod_{i=1}^{k_z}\frac{1}{1+h(\frac{r_z}{r_n})^{-\eta}}\Bigg)\frac{1}{(1+h)^{k_n-1}}
\end{aligned} \tag{15}$$

Removing the condition on $k_1, \cdots, k_{n-1}, k_n, k_{n+1}, \cdots, k_N$, we can get the probability that a packet from zone n can be successfully received in the presence of interfering signals mathematically:

$$p_{suc,n} = \sum_{k_1=0}^{X_1}\cdots\sum_{k_{n-1}=0}^{X_{n-1}}\sum_{k_n=1}^{X_n}\sum_{k_{n+1}=0}^{X_{n+1}}\cdots\sum_{k_N=0}^{X_N}\Bigg(p_{s,n}(\mathbf{k})\prod_{m=1}^{N}P_{k_m}\Bigg) \tag{16}$$

If any transmission cannot capture the channel, transmission error happens. The transmission error probability can be computed as follows:

$$p_{fal} = p_{falall} - p_{fal0} - p_{suc1} \tag{17}$$

where p_{falall} is the probability sum of three types of situation. They include transmission error, no packet sent and only one packet sent; p_{fal0} is the probability that there is no packet sent;

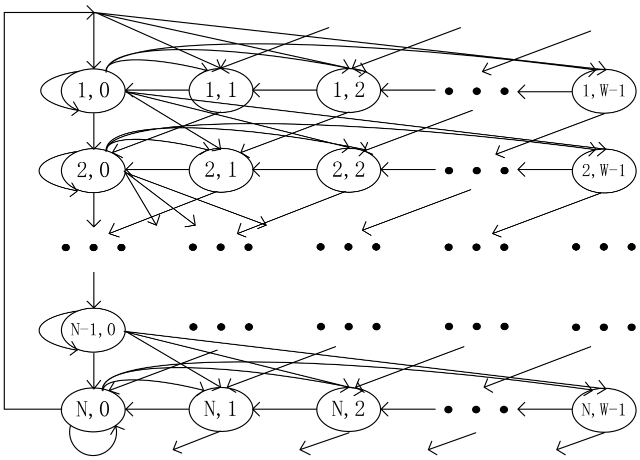

FIGURE 3. Two-dimensional Markov chain for V2I encountering model.

and p_{suc1} is the probability that there is only one packet sent. The three probabilities can be expressed as,

$$p_{falall} = \sum_{k_1=0}^{X_1} \cdots \sum_{k_{n-1}=0}^{X_{n-1}} \sum_{k_n=0}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_N=0}^{X_N} \times \left(\prod_{n=1}^{N} (1 - p_{s,n}(\mathbf{k}))^{k_n} \prod_{n=1}^{N} P_{k_n} \right) \tag{18}$$

$$p_{fal0} = \prod_{i=1}^{N} (1 - \tau_n)^{X_i} \tag{19}$$

$$p_{suc1} = \sum_{n=1}^{N} \left(P_{k_n=1} \prod_{m=1, m \neq n}^{N} P_{k_m=0} \right) \tag{20}$$

E. EMBEDDED MARKOV CHAIN

To study the throughput performance of MAC in each zone, we examine a random vehicle node i and express its state by a two-dimensional Markov chain $\{z(t), b(t)\}$ embedded at the commencement of backoff intervals, where $z(t)$ standing for the zone which the vehicle node is currently in, and $b(t)$ standing for its backoff counter at time slot t. In Fig. 3, the first row of states, indexed $(1, 0)$ to $(1, W-1)$, represents the backoff states when vehicle nodes are in the zone 1. The next row of states, indexed $(2, 0)$ to $(2, W-1)$, represents the backoff states when vehicle nodes are in the zone 2. And the last row of states, indexed $(N, 0)$ to $(N, W-1)$, represents the backoff states when vehicle nodes are in the zone N.

The state space of the two-dimensional Markov chain is shown in Fig. 3 with the non-null transition probabilities from t to $t+1$ given by the following equations:

$$P\{(n, k)|(n, k+1)\} = 1 - \frac{E[T_{dec}]}{t_n}, \quad k \in [0, W-2], \tag{21}$$

where $E[T_{dec}]$ is the mean time it takes for vehicle node i's backoff interval to decrease by one. (21) gives the probability that vehicle node i remains in its current zone after the backoff time is decreased by one, and $E[T_{dec}]/t_n$ is the probability that vehicle node i instead moves from the zone n to zone $n+1$.

$$P\{(n, k)|(n-1, k+1)\} = \frac{E[T_{dec}]}{t_{n-1}}, \quad k \in [0, W-2], \tag{22}$$

The equation represents the probability that vehicle node i moves to the next zone after a backoff countdown. When $n = 1$, we look upon zone $n-1$ as zone N in computing the probability.

The probability that vehicle node i sends one packet and starts a new round of backoff, while remaining in its current zone is given by,

$$P\{(n, k)|(n, 0)\} = Pr\{x = k\} \left(1 - \frac{E[T_{x_n}]}{t_n} \right), \quad k \in [0, W-1], \tag{23}$$

where T_{x_n} is the transmission time of one packet. The new backoff interval is selected according to the p-persistent CSMA.

The probability that vehicle node i travels to the next zone after a transmission is given by,

$$P\{(n, k)|(n-1, 0)\} = Pr\{x = k\} \frac{E[T_{x_{n-1}}]}{t_{n-1}}, k \in [0, W-1], \tag{24}$$

As for (22), when $n = 1$, zone $n-1$ is still regarded as zone N.

Let $\pi_{n,k} = \lim_{t \to \infty} Pr\{z(t) = n, b(t) = k\}$ be the steady state probability of the Markov chain and π the corresponding $(N \times W)$ vector, such that $\boldsymbol{\pi} = [\pi_{1,0}, .., \pi_{1,W-1}, .., \pi_{N,0}, .., \pi_{N,W-1}]$. Given the state transition probability matrix $\mathbf{P}$ with each non-null element shown in (21), (22), (23) and (24), $\pi_{n,k}$ could be derived according to following balance equations

$$\begin{cases} \boldsymbol{\pi} \mathbf{P} = \boldsymbol{\pi}, \\ \sum_{n=1}^{N} \sum_{k=0}^{W-1} \pi_{n,k} = 1, \end{cases} \tag{25}$$

To solve (25), we denote by τ_n the conditional transmission probability given that the transmitting nodes are located in zone n. We have

$$\tau_n = \frac{\pi_{n,0}}{\sum_k \pi_{n,k}}, n \in \mathbb{Z}, \tag{26}$$

where $\pi_{n,0}$ is the joint probability that nodes are located in zone n and send one packet; $\pi_{n,k}$ is the steady probability that nodes are located in zone n while backoff counter is k, $0 \le k \le W-1$.

F. MEAN TIME OF ONE BACKOFF INTERVAL $E[T_{dec}]$ AND MEAN TRANSMISSION TIME $E[T_{x_n}]$

Since we consider capture effect in the paper, the equations for $E[T_{dec}]$ and $E[T_{x_n}]$ are substantially different from those in [8]. We cannot only consider successful transmission when there is one packet transmitted, but we also need to consider successful transmission when there are more than one packet transmitted. So it is more complicated.

1) MEAN TIME OF ONE BACKOFF INTERVAL $E[T_{dec}]$

We first consider the mean time for node i to decrement its backoff interval by one. The successful transmission time $T_{suc,n}$ and the failed transmission time $T_{col,n}$ in zone n is as follows:

$$T_{suc,n} = \frac{L}{pt_n} + SIFS + \frac{ACK}{pt_n} + DIFS \tag{27}$$

$$T_{col,n} = \frac{L}{pt_n} + EIFS \tag{28}$$

As such, the successful transmission time $T_{suc,n}$ is longer than the failed transmission time $T_{col,n}$ when the payload transmission rate is the same. However, when there are transmissions from different zones, the longest transmission is from the zone which is the farthest zone from the RSU regardless of whether the transmission is successful or fails, given the parameters used in this paper, such as payload transmission rate pt_n, packet size L, SIFS, DIFS and ACK. In other words, the failed transmission time $T_{col,n}$ in zone n is longer than the successful transmission time $T_{suc,m}$ in zone m if zone n is farther than zone m from the RSU. Mathematically, we have

$$E[T_{dec}] = P_e\delta + E[T_{suc}] + E[T_{mix}] \tag{29}$$

where P_e is the probability that there is no transmission and the channel is idle; $E[T_{suc}]$ is the mean time when there is either only one packet transmitting or there are several packets transmitting and the successful transmission is in the zone which is the farthest zone from the RSU and $E[T_{mix}]$ is the mean time when there are no successful transmission or there is successful transmission but the successful transmission is not in the zone which is the farthest zone from the RSU under the condition of several transmissions.

The probability P_e can be calculated as

$$P_e = \prod_{n=1}^{N} (1 - \tau_n)^{X_n} \tag{30}$$

The mean time $E[T_{suc}]$ can be computed as

$$E[T_{suc}] = \sum_{n=1}^{N} p_{dsuc,n} T_{suc,n} \tag{31}$$

where $p_{dsuc,n}$ is the probability that there is only one packet transmitting in zone n or there are several packets transmitting and the successful and longest transmission is in the zone n and it can be expressed as

$$p_{dsuc,n} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_{n_{map}-1}=0}^{X_{n_{map}-1}} \sum_{k_{n_{map}}=0}^{X_{n_{map}}} \times \Big(p_{s,n}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{n-1}=0} P_{k_n} \cdots P_{k_{n_{map}}} P_{k_{n_{map}+1=0}} \cdots P_{k_N=0} \Big) \tag{32}$$

The mean time $E[T_{mix}]$ can be computed as

$$E[T_{mix}] = \sum_{n=1}^{\lfloor \frac{N+1}{2} \rfloor} (p_{ss,n} + p_{f,n}) T_{col,n} \tag{33}$$

where $p_{ss,n}$ is the probability that there are several packets transmitting, with the longest transmission in zone n, but the successful transmission coming from a zone that is closer to the RSU; $p_{f,n}$ is the probability that there are several packets transmitting, with the farthest transmission coming from zone n, and no transmission is successful.

The probability $p_{ss,n}$ can be decomposed as

$$p_{ss,n} = \sum_{i=n+1}^{n_{map}-1} p_{s,n,i}, \tag{34}$$

where $p_{s,n,i}$ is the probability that one packet from zone i is transmitted successfully but the longest transmission is in zone n or zone n_{map}. $p_{s,n,i}$ can be further decomposed as

$$p_{s,n,i} = p^{only}_{n,i} + p^{only}_{n_{map},i} + p_{n,n_{map},i} \tag{35}$$

where $p^{only}_{n,i}$ is the probability that one packet from zone i is transmitted successfully but the longest transmission is in only zone n; $p^{only}_{n_{map},i}$ is the probability that one packet from zone i is transmitted successfully but the longest transmission is in only zone n_{map} and $p_{n,n_{map},i}$ is the probability that one packet from zone i is transmitted successfully but the longest transmission is in both zone n and zone n_{map}. The three probabilities can be expressed as follows:

$$p^{only}_{n,i} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_i=1}^{X_i} \cdots \sum_{k_{n_{map}-1}=0}^{X_{n_{map}-1}} \times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{n-1}=0} P_{k_n} \cdots P_{k_{n_{map}-1}} P_{k_{n_{map}}=0} \cdots P_{k_N=0} \Big) \tag{36}$$

$$p^{only}_{n_{map},i} = \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_i=1}^{X_i} \cdots \sum_{k_{n_{map}-1}=0}^{X_{n_{map}-1}} \sum_{k_{n_{map}}=1}^{X_{n_{map}}} \times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_n=0} P_{k_{n+1}} \cdots P_{k_{n_{map}}} P_{k_{n_{map}+1}=0} \cdots P_{k_N=0} \Big) \tag{37}$$

$$p_{n,n_{map},i} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_i=1}^{X_i} \cdots \sum_{k_{n_{map}-1}=0}^{X_{n_{map}-1}} \sum_{k_{n_{map}}=1}^{X_{n_{map}}} \times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{n-1}=0} P_{k_n} \cdots P_{k_{n_{map}}} P_{k_{n_{map}+1}=0} \cdots P_{k_N=0} \Big) \tag{38}$$

The probability $p_{f,n}$ can be described as

$$p_{f,n} = p^{only}_{fal,n} + p^{only}_{fal,n_{map}} + p_{fal,n,n_{map}} \tag{39}$$

where $p^{only}_{fal,n}$ is the probability that all transmissions failed and the longest transmission is in zone n only; $p^{only}_{fal,n_{map}}$ is the probability that all transmissions failed and the longest transmission is in zone n_{map} only and $p_{fal,n,n_{map}}$ is the probability that all transmissions failed and the longest transmission is in both zone n and zone n_{map}. They can be computed as

$$p_{fal,n}^{only} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_{nmap-1}=0}^{X_{nmap-1}} \times \Big((1-p_{s,n}(\mathbf{k}))^{k_n}(1-p_{s,n+1}(\mathbf{k}))^{k_{n+1}} \cdots \times (1-p_{s,n_{map}-1}(\mathbf{k}))^{k_{nmap-1}} P_{k_n}P_{k_{n+1}} \cdots P_{k_{nmap-1}}\Big) - \sum_{k_n=1}^{X_n}\Big((1-p_{s,n}(\mathbf{k}))^{k_n} P_{k_n} P_{k_{n+1}=0} \cdots P_{k_{nmap-1}=0}\Big) \tag{40}$$

$$p_{fal,n_{map}}^{only} = \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_{nmap-1}=0}^{X_{nmap-1}} \sum_{k_{nmap}=1}^{X_{nmap}} \times \Big((1-p_{s,n+1}(\mathbf{k}))^{k_{n+1}} \cdots (1-p_{s,n_{map}-1}(\mathbf{k}))^{k_{nmap-1}} \times (1-p_{s,n_{map}}(\mathbf{k}))^{k_{nmap}} P_{k_{n+1}} \cdots P_{k_{nmap-1}} P_{k_{nmap}}\Big) - \sum_{k_{nmap}=1}^{X_{nmap}} \Big((1-p_{s,n_{map}}(\mathbf{k}))^{k_{nmap}} P_{k_{nmap}} P_{k_{n+1}=0} \cdots P_{k_{nmap-1}=0}\Big) \tag{41}$$

$$p_{fal,n,n_{map}} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_{nmap-1}=0}^{X_{nmap-1}} \sum_{k_{nmap}=1}^{X_{nmap}} \times \Big((1-p_{s,n}(\mathbf{k}))^{k_n} \cdots (1-p_{s,n_{map}-1}(\mathbf{k}))^{k_{nmap-1}} (1-p_{s,n_{map}}(\mathbf{k}))^{k_{nmap}} P_{k_n}P_{k_{n+1}} \cdots P_{k_{nmap}}\Big) \tag{42}$$

2) MEAN TRANSMISSION TIME $E[T_{x_n}]$

The expected mean transmission time $E[T_{x_n}]$ of node i which is in zone n is as follows:

$$E[T_{x_n}] = E[T_n] + E[T_{out,n}] \tag{43}$$

where $E[T_n]$ is the mean transmission time that the longest transmission time from zone n, and $E[T_{out,n}]$ is the mean transmission time that the longest transmission time from the zone which is farther than zone n from RSU when one packet is transmitting in zone n.

The mean transmission time $E[T_n]$ can be regraded as two parts: (1) the successful transmission is from zone n; (2) the transmission from zone n fails; and can be expressed as

$$E[T_n] = E[T_n^{suc}] + E[T_n^{fal}] \tag{44}$$

where $E[T_n^{suc}]$ is the mean time that the longest and successful transmission is from zone n, and $E[T_n^{fal}]$ is the mean time that the longest transmission is from zone n but there is no successful transmission in zone n. The two mean time can be computed as

$$E[T_n^{suc}] = p_{dsuc,n} T_{suc,n} \tag{45}$$

where $T_{suc,n}$ and $p_{dsuc,n}$ are as same as those in (27) and (32).

$$E[T_n^{fal}] = (p_{fsuc,n} + p_{ffal,n}) T_{col,n} \tag{46}$$

where $p_{fsuc,n}$ is the probability that the longest transmission is from zone n and there is successful transmission but the successful transmission is from zone i which is nearer than zone n from the RSU; $p_{ffal,n}$ is the probability that the longest transmission is from zone n and there is no successful transmission. The two probabilities can be expressed as follows:

$$p_{fsuc,n} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_i=1}^{X_i} \cdots \sum_{k_{nmap}=0}^{X_{nmap}} \times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{n-1}=0} P_{k_n} \cdots P_{k_{nmap}} P_{k_{nmap+1}=0} \cdots P_{k_N=0}\Big), \quad n+1 \le i \le n_{map} \tag{47}$$

$$p_{ffal,n} = \sum_{k_n=1}^{X_n} \sum_{k_{n+1}=0}^{X_{n+1}} \cdots \sum_{k_{nmap}=0}^{X_{nmap}} \times \Big((1-p_{s,n}(\mathbf{k}))^{k_n}(1-p_{s,n+1}(\mathbf{k}))^{k_{n+1}} \cdots (1-p_{s,n_{map}}(\mathbf{k}))^{k_{nmap}} P_{k_n}P_{k_{n+1}} \cdots P_{k_{nmap}}\Big) - \sum_{k_n=1}^{X_n} \Big((1-p_{s,n}(\mathbf{k}))^{k_n} P_{k_n} P_{k_{n+1}=0} \cdots P_{k_{nmap}=0}\Big) \tag{48}$$

The mean transmission time $E[T_{out,n}]$ can be written as

$$E[T_{out,n}] = \sum_{m=1}^{n-1} E[T_{m,n}] \tag{49}$$

where $E[T_{m,n}]$ is the mean time that the longest transmission is from zone m or m_{map} and there is at least one transmission in zone n, where $m < n$.

$E[T_{m,n}]$ can be expressed as

$$E[T_{m,n}] = E[T_{m,n}^{suc}] + E[T_{m,n}^{fal}] \tag{50}$$

where $E[T_{m,n}^{suc}]$ is the mean time that the longest and successful transmission is from zone m and there is at least one transmission in zone n, and $E[T_m^{fal}]$ is the mean time that there is at least one transmission in zone n and the longest transmission is from zone m but there is no successful transmission in zone m. They can be calculated as

$$E[T_{m,n}^{suc}] = p_{m,n}^{suc} T_{suc,m} \tag{51}$$

where $T_{suc,m}$ is from (27) and $p_{m,n}^{suc}$ is similar to (32) and can be described as

$$p_{m,n}^{suc} = \sum_{k_m=1}^{X_m} \sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_n=1}^{X_n} \cdots \sum_{k_{mmap-1}=0}^{X_{mmap-1}} \sum_{k_{mmap}=0}^{X_{mmap}} \times \Big(p_{s,n}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{m-1}=0} P_{k_m} \cdots P_{k_{mmap}} P_{k_{mmap+1=0}} \cdots P_{k_N=0}\Big) \tag{52}$$

$$E[T_{m,n}^{fal}] = (p_{m,n}^{s} + p_{m,n}^{f}) T_{col,m} \tag{53}$$

where $p_{m,n}^{s}$ is the probability that there are several packets transmitting and the longest transmission is in zone m and the successful transmission from the zone which is nearer than zone m from the RSU; $p^f_{m,n}$ is the probability that there are several packets transmitting and no transmission is successful. The probability $p^s_{m,n}$ can be expressed as

$$p^s_{m,n} = \sum_{i=m+1}^{m_{map}-1} p^n_{m,i}, \tag{54}$$

where $p^n_{m,i}$ is the probability that there is at least one transmission in zone n and one packet from zone i is transmitted successfully but the longest transmission is in zone m or zone m_{map} and it can be mathematically

$$p^n_{m,i} = p^{n,only}_{m,i} + p^{n,only}_{m_{map},i} + p^n_{m,m_{map},i} \tag{55}$$

where $p^{n,only}_{m,i}$ is the probability that there is at least one packet transmitting in zone n and one packet from zone i is transmitted successfully but the longest transmission is in only zone m; $p^{n,only}_{m_{map},i}$ is the probability that there is at least one packet transmitting in zone n and one packet from zone i is transmitted successfully but the longest transmission is in only zone m_{map} and $p^n_{m,m_{map},i}$ is the probability that there is at least one packet transmitting in zone n and one packet from zone i is transmitted successfully but the longest transmission is in both zone m and zone m_{map}. The three probabilities are similar to (36), (37) and (38) and can be expressed as follows:

$$\begin{aligned} p^{n,only}_{m,i} = &\sum_{k_m=1}^{X_m} \sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_n=1}^{X_n} \cdots \sum_{k_{n_{map}-1}=0}^{X_{n_{map}-1}} \\ &\times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{m-1}=0} P_{k_n} \cdots P_{k_{m_{map}-1}} \\ &\quad P_{k_{m_{map}}=0} \cdots P_{k_N=0} \Big) \end{aligned} \tag{56}$$

$$\begin{aligned} p^{n,only}_{m_{map},i} = &\sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_n=1}^{X_n} \cdots \sum_{k_{m_{map}-1}=0}^{X_{m_{map}-1}} \sum_{k_{m_{map}}=1}^{X_{m_{map}}} \\ &\times \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_m=0} P_{k_{m+1}} \cdots P_{k_{m_{map}}} \\ &\quad P_{k_{m_{map}+1}=0} \cdots P_{k_N=0} \Big) \end{aligned} \tag{57}$$

$$\begin{aligned} p^n_{m,m_{map},i} = &\sum_{k_m=1}^{X_m} \sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_n=1}^{X_n} \cdots \sum_{k_{m_{map}-1}=0}^{X_{m_{map}-1}} \\ &\times \sum_{k_{m_{map}}=1}^{X_{m_{map}}} \Big(p_{s,i}(\mathbf{k}) P_{k_1=0} \cdots P_{k_{m-1}=0} P_{k_n} \cdots P_{k_{m_{map}}} \\ &\quad P_{k_{m_{map}+1}=0} \cdots P_{k_N=0} \Big) \end{aligned} \tag{58}$$

The probability $p^f_{m,n}$ be described as

$$p^f_{m,n} = p^{n,only}_{f,m,i} + p^{n,only}_{f,m_{map},i} + p_{f,m,m_{map},i} \tag{59}$$

where $p^{n,only}_{f,m,i}$ is the probability that the longest transmission is in zone m only and there is at least one transmission in zone n and all transmissions failed; $p^{n,only}_{f,m_{map},i}$ is the probability that the longest transmission is in zone m_{map} only, there is at least one transmission in zone n, and all transmissions failed and $p_{f,m,m_{map},i}$ is the probability that the longest transmission is in both zone m and zone m_{map} and there is at least one transmission in zone n and all transmissions failed. They can be computed as

$$\begin{aligned} p^{n,only}_{f,m,i} = &\sum_{k_m=1}^{X_m} \sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_n=1}^{X_n} \cdots \sum_{k_{m_{map}-1}=0}^{X_{m_{map}-1}} \\ &\times \Big((1-p_{s,m}(\mathbf{k}))^{k_m} (1-p_{s,m+1}(\mathbf{k}))^{k_{m+1}} \cdots \\ &\quad (1-p_{s,m_{map}-1}(\mathbf{k}))^{k_{m_{map}-1}} P_{k_m} P_{k_{m+1}} \cdots P_{k_{m_{map}-1}} \Big) \end{aligned} \tag{60}$$

$$\begin{aligned} p^{n,only}_{f,m_{map},i} = &\sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_{m_{map}-1}=0}^{X_{m_{map}-1}} \sum_{k_{m_{map}}=1}^{X_{m_{map}}} \\ &\times \Big((1-p_{s,m+1}(\mathbf{k}))^{k_{m+1}} \cdots (1-p_{s,m_{map}-1}(\mathbf{k}))^{k_{m_{map}-1}} \\ &\quad (1-p_{s,m_{map}}(\mathbf{k}))^{k_{m_{map}}} P_{k_{m+1}} \cdots P_{k_{m_{map}-1}} P_{k_{m_{map}}} \Big) \\ &- \sum_{k_{m_{map}}=1}^{X_{m_{map}}} \Big((1-p_{s,m_{map}}(\mathbf{k}))^{k_{m_{map}}} \\ &\quad P_{k_{m_{map}}} P_{k_{m+1}=0} \cdots P_{k_{m_{map}-1}=0} \Big) \end{aligned} \tag{61}$$

$$\begin{aligned} p_{f,m,m_{map},i} = &\sum_{k_m=1}^{X_m} \sum_{k_{m+1}=0}^{X_{m+1}} \cdots \sum_{k_{m_{map}-1}=0}^{X_{m_{map}-1}} \sum_{k_{m_{map}}=1}^{X_{m_{map}}} \\ &\times \Big((1-p_{s,m}(\mathbf{k}))^{k_m} \cdots (1-p_{s,m_{map}-1}(\mathbf{k}))^{k_{m_{map}-1}} \\ &\quad (1-p_{s,m_{map}}(\mathbf{k}))^{k_{m_{map}}} P_{k_m} P_{k_{m+1}} \cdots P_{k_{m_{map}}} \Big) \end{aligned} \tag{62}$$

G. THROUGHPUT ANALYSIS

We use the normalized nodal throughput and system throughput to evaluate the performance of Drive-thru Internet with Rayleigh capture as defined in [8].

The normalized nodal throughput in the zone n, s_n, is defined as the amount of packet payload sent in a unit time slot, given by

$$s_n = \frac{\tau_n p_{suc} L}{(1-\tau_n)E[T_{dec}] + \tau_n E[T_{x_n}]} \tag{63}$$

With X_n nodes presenting in zone n, the integrated throughput of the whole network, S, is

$$S = \sum_{n=1}^{N} X_n s_n \tag{64}$$

V. SIMULATION VALIDATION AND PERFORMANCE EVALUATION

A. SIMULATION SETUP

Using a discrete event simulator coded in C++, we validate the prediction results based on simulations. We simulate a

TABLE 1. Parameter of zones

Zone n	0	1	2	3	4	5	6	7
r_n (m)	20	25	30	40	60	40	30	25
pt_n (Mbps)	0	1	2	5.5	11	5.5	2	1
$CW_{min,n}$	Inf	512	256	128	64	128	256	512

TABLE 2. DCF parameters.

Parameter	Value
Timeslot size, δ	50 us
SIFS	50 us
DIFS	128 us
EIFS	216 us
Propagation delay, σ	1 us
ACK	38 bytes

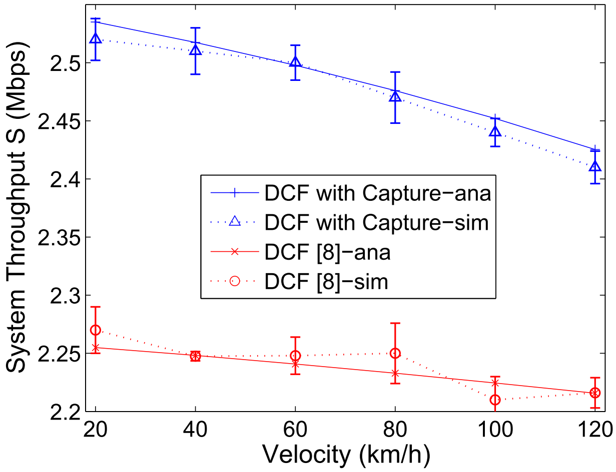

FIGURE 4. System throughput under different velocities with CWs shown in Table 1 with the constant network size $X = 50$.

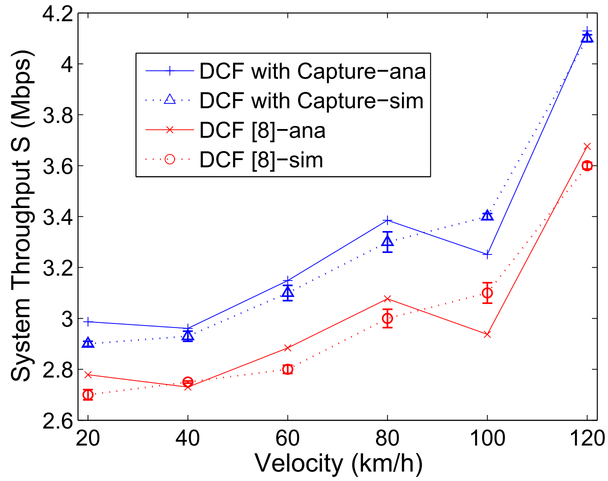

FIGURE 5. System throughput under different velocities with CWs shown in Table 1 with vehicular traffic flow model.

Drive-Thru Internet scenario as shown in Fig. 1, in which the vehicle nodes compete for wireless channel with IEEE 802.11b. Unless otherwise mentioned, we use the vehicular traffic flow model, in which vehicle nodes move at the constant velocity v and the number of vehicle nodes is determined by v. Once leaving the RSU, a vehicle node reenters the RSU as a new vehicle node. The whole area is divided into 8 spatial zones as specified in Table 1. The length and data rates of each zone are based on the extensive measurements reported in [1]. Parameters of the DCF are given in Table 2, and are used for both simulations and analysis. For each experiment, we carry out 30 simulation runs and plot the results with the 95% confidence interval.

B. MODEL COMPARISONS

Fig. 4 shows system throughput comparison between self-adaptive DCF with capture effect in a non-ideal channel and DCF proposed in [8] under different velocities with the constant network size $X = 50$. Our 2-D model predictions match the simulations accurately. It can be seen that system throughput of both DCFs decrease slowly as traveling velocity increase. This reveals that velocity increase affects the success of packet delivery. Similar to HHSC scheme in [9], system throughput of both self-adaptive DCFs decrease relatively slowly to the legacy IEEE 802.11 DCF as described in [9, Fig. 6]. Under certain velocity, self-adaptive DCF with the capture effect in a non-ideal channel can obtain higher system throughput than DCF proposed in [8]. This is because the capture effect can cause one of multiple concurrent transmissions (particularly, the transmission with highest power at the receiver) to capture the channel and be successfully received. We can see that it is appropriate to include the capture effect when modelling complicated vehicular environments in which there is Rayleigh fading.

C. PERFORMANCE EVALUATION

In the subsection, we mainly evaluate the performance of self-adaptive DCF with capture effect in a non-ideal channel with vehicular traffic flow model in Drive-Thru Internet scenario.

Fig. 5 shows system throughput comparison between self-adaptive DCF with capture effect in a non-ideal channel and DCF proposed in [8] under different velocities with vehicular traffic flow model. Our 2-D model predictions match the simulations accurately. It can be seen that system throughput of both DCFs increase as traveling velocity increase. This is contrary to that in Fig. 4. Because in Fig. 4, the network size is constant ($X = 50$), while in Fig. 5, the network size decreases as traveling velocity increases based on (4) and (6). This is proved by vehicular traffic flow model and Little's law. Combining equations (4) with (6), we can get,

$$X = \left(1 - \frac{v}{v_f}\right) \times k_{jam} \times \left(\sum_{n \in \mathbb{A}} r_n\right) - 1, \qquad (65)$$

From (65), we can clearly see that when traveling velocity increases, the network size decreases. In [9], we have noticed that self-adaptive DCF is more sensitive to network size than to traveling velocity, so this is reason that system throughput increases when traveling velocity increases and network size decreases. Similar to Fig. 4, under certain velocity, self-adaptive DCF with capture effect in a non-ideal channel can

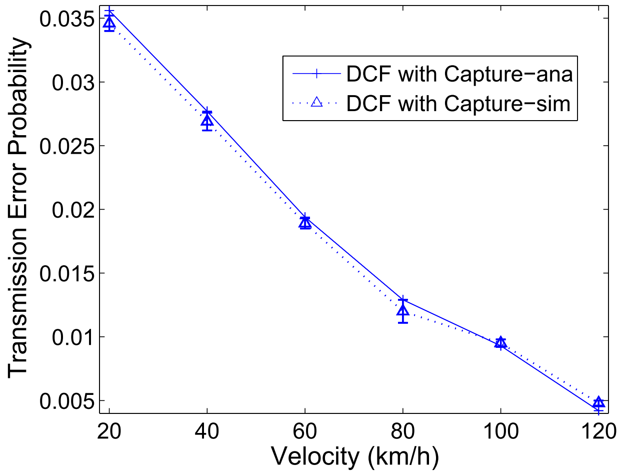

FIGURE 6. Transmission error probability under different velocities with CWs shown in Table 1 with vehicular traffic flow model.

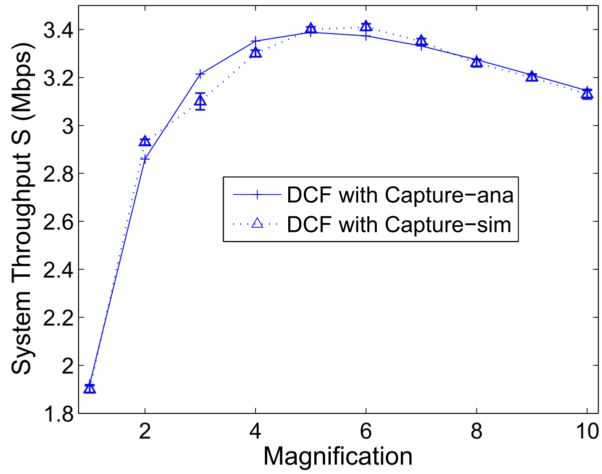

FIGURE 8. System throughput under constant velocity with variable CWs with vehicular traffic flow model.

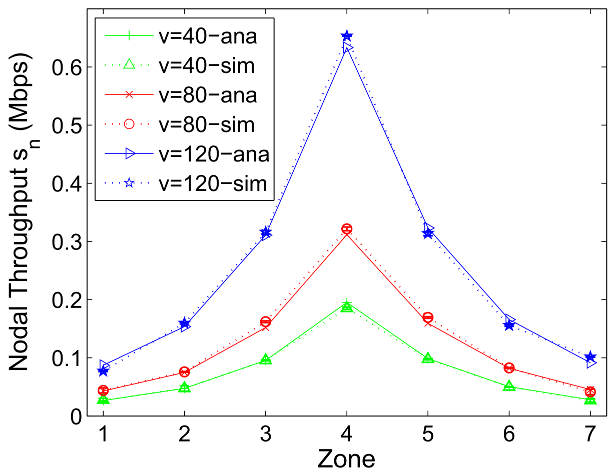

FIGURE 7. Nodal throughput under different velocities with CWs shown in Table 1 with vehicular traffic flow model in different zones.

obtain higher system throughput than DCF proposed in [8] due to capture effect.

Fig. 6 shows transmission error probability of self-adaptive DCF with capture effect in a non-ideal channel under different velocities with vehicular traffic flow model. Our 2-D model predictions match the simulations accurately. We can see that transmission error probability of DCFs decrease linearly as traveling velocity increase. When traveling velocity increases, the network size decreases based on vehicular traffic flow model, and then interference and collision from concurrent transmissions decrease. So the transmission error probability decreases as well. This tendency of transmission error probability is consistent with that of system throughput in Fig. 5. Larger transmission error probability results in smaller system throughput and smaller transmission error probability results in larger system throughput.

Fig. 7 shows nodal throughput comparison of self-adaptive DCF with capture effect in a non-ideal channel under different velocities with vehicular traffic flow model. Our 2-D model predictions match the simulations accurately. The nodal throughput is a bell-shaped, which results from the nodes close to RSU having smaller CWs and accordingly higher probabilities to acquire the channel as also seen in [8, Figs. 3 and 4]. This self-adaptive characteristic overcomes the performance abnormal [23], and then increases system throughput. For different traveling velocities, nodal throughput is different. The larger the average traveling velocity is, the larger the average nodal throughput is. This is consistent with Fig. 5 and Fig. 6. Compared to [8, Fig. 4], nodal throughput intervals among different velocities are larger under the influence of the capture effect and network size. We also notice that the bell-shaped curve is not symmetric, although the length, the data rate and CW_{min} of zones are all axis symmetric about the RSU. The symmetry can be seen from Table 1. In particular, zones in the departing direction achieve larger nodal throughput compared with those in the arrival direction. This phenomenon has been observed and explained in [8]. However, the phenomenon is not very obvious when the capture effect is modelled. Our modelling reveals that the capture effect in a non-ideal channel reduces the transmission error probability, increases throughput, and reduces the asymmetry in the bell-shaped throughput curve.

Fig. 8 shows system throughput of self-adaptive DCF with capture effect in a non-ideal channel under constant traveling velocity with variable CWs with vehicular traffic flow model. Here, we set the basic CWs as $CW_{min,n} = \{128, 64, 32, 16, 32, 64, 128\}$, $1 \leq n \leq N$. Let W be magnification of $CW_{min,n}$, where $1 \leq W \leq 10$ and then $CWs = CW_{min,n} \times W$. The constant traveling velocity is set as 80 km/h. It can be seen that there is a very close match between our 2-D model predictions (solid line) and the simulation results (dotted line). System throughput of self-adaptive DCF with capture effect in a non-ideal channel first increases and then decreases as the magnification W increases. We can notice that when magnification is smaller, $1 \leq W \leq 4$, system throughput rise sharply with W; when magnification is larger, $4 \leq W \leq 6$, system throughput reaches saturation value and level off basically; finally when magnification is larger than 6, system throughput decreases slowly. This is because at smaller magnification, $CW_{min,n}$ is also smaller and collision from concurrent transmissions is more; when magnification is larger, $CW_{min,n}$ is also larger and it alleviates collision from concurrent transmissions; when magnification continues to become larger, the effect of further alleviating collisions is outweighed by the delays to packet delivery. Under smaller $CW_{min,n}$, it may save some time to send packets, but it produces more collisions; Under larger $CW_{min,n}$, it can alleviate collision and provide larger throughput but it spends more time. From this figure, we can see appropriate magnification, $W = 4$, is preferable, which is the $CW_{min,n}$ we use in this paper and that used in [1].

VI. CONCLUSION

In this paper, we presented a 2-D Markov chain performance-prediction model for analysing the performance of Drive-thru Internet with Rayleigh capture. Our 2-D model incorporates both the capture effect into a 2-D Markov Chain modeling the high-node mobility and broadcast DCF. The model was validated in a variety of network scenarios, with extensive simulation results demonstrating that the model accurately predicts network performance.

The performance-prediction model unveils the impacts of number of vehicles and mobility velocity on the throughput in a Rayleigh capture channel. We use a vehicular traffic flow model to predict vehicular movement on road by aggregating all vehicles into a flow. We demonstrate that using our obtained optimal contention window value can reach the best system throughput without wasting contention time.

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