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Throughput and Fairness Analysis of 802.11-based Vehicle-to-Infrastructure Data Transfers

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***Abstract*—The performance of vehicular Internet access using roadside 802.11-based APs has been extensively studied in the literature. However, much less attention has been dedicated to analysing the maximum achievable throughput when multiple vehicles simultaneously share the bandwidth of the same roadside AP in a given mobility scenario. To fill such a gap, in this paper we develop an analytical framework to quantify the total amount of data transferred by a vehicle that drives through the coverage area of a roadside 802.11-based AP. The distinctive aspects of our analysis are the following: (i) it considers heterogeneous vehicular environments where vehicles may have different mobility characteristics; and (ii) it accurately takes into account critical traffic parameters, such as road capacity and vehicle density, when modelling MAC-layer capacity. Our model is able to accurately characterize the unfairness that may arise due to differences in the relative speed of vehicles. In addition, our analysis and the supporting simulation results are useful to explain the complex relationship that exists between the upload capacity per vehicle, the macroscopic characteristics of the traffic stream, the vehicular mobility model, and the 802.11 channel access rules.**

***Keywords*-Vehicular Internet access, 802.11 MAC protocol, performance analysis, vehicular mobility models.**

I. Introduction

Over the past few years we have seen an impressive proliferation of large-scale 802.11-based networks. Thus, the idea of using roadside 802.11 access points (APs) to provide network coverage to highly mobile users travelling in cars, has gained significant momentum. Furthermore, the availability of vehicle-to-infrastructure (V2I) communication capabilities can pave the way to novel types of applications for vehicles, involving both data downloads to moving vehicles (e.g., enhanced local maps with traffic and touristic information), and data uploads from moving vehicles (e.g., measurements collected by on-board sensors, video clips taken from on-board cameras during the trip, etc.) [1]–[4].

Prior papers have experimentally investigated the performance of vehicular Internet access using roadside 802.11-based APs, and whether or not this performance would be adequate for certain applications [1], [5]–[7]. These studies have demonstrated the feasibility of using IEEE 802.11 technologies to support connectivity at typical vehicular speeds, with acceptable durations of AP associations and reasonable data transfers. However, much less attention has been dedicated to evaluating the impact on the network performance of the contention due to multiple vehicles simultaneously accessing a roadside AP in a given mobility scenario. Thus, key open questions addressed in this paper are the following: *what is the theoretically achievable network throughput of a single roadside AP in a given mobility scenario*? *what is the effect of macroscopic vehicular traffic parameters*, such as vehicle density, road capacity, absolute and relative vehicles' speeds, *on the upload capacity per vehicle*? To better understand the importance of these questions, let us consider the fairness problem which may affect V2I communications when vehicles having different speeds communicate with the same roadside AP [8]. Intuitively, the duration of the connectivity with the AP depends on the vehicle speed. However, the total amount of data that the moving vehicle can transfer to the roadside AP is not necessarily an increasing function of the vehicle's sojourn time in the AP's coverage area, because it may be affected by other factors, such as the mobility patterns of other contending vehicles.

It is worth pointing out that the performance analysis of the IEEE 802.11 MAC protocol has received a significant attention in the past decade, and remarkably accurate models are available to evaluate throughput and delay performance of single-cell WLANs under stationary conditions [9]–[12]. However, as a matter of fact, the vehicular environment poses new challenges due to its unique characteristics, which are not addressed by existing models. For instance, high-speed mobility may cause frequent variations of node density under the AP's coverage area, which affect the shared channel capacity. In addition, the dependence of vehicular mobility on macroscopic traffic characteristics, such as vehicle density or road capacity, further complicates the analysis of the channel access dynamics. To the best our knowledge, [13] is one of the first papers developing analytical models to quantify the impact of parameters such as road traffic density and vehicle speed on the download performance of moving vehicles connected to a roadside access point. However, the analysis in [13] does not directly apply to 802.11-based APs because it is developed for a

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collision-free MAC protocol. The model in [14] is the closest to our work because it analyses the impact of vehicle density and speed on the performance of V2I communications using 802.11-like technologies. However, authors in [14] consider only homogeneous vehicular environments, and they do not accurately model the impact of road capacity on the network performance.

To address the above issues, in this paper we develop an analytical framework to quantify the total amount of data transferred by a vehicle that drives through the coverage area of a roadside 802.11-based AP. The distinctive aspects of our analysis are the following: (i) *it considers heterogeneous vehicular environments where vehicles may have different mobility characteristics*, which allows us to precisely characterize the unfairness that may arise due to differences in the relative speeds of vehicles; and (ii) *it accurately takes into account critical traffic parameters*, such as road capacity and vehicle density, *when modelling MAC-layer capacity*.

For the purpose of evaluation, in this study we describe the vehicular movements using two speed models commonly adopted for uninterrupted traffic flows (i.e., in the absence of external factors, such as traffic lights, stop signs or intersections, which can perturb the traffic stream), namely the Constant Speed Motion (CSM) model and the Fluid Traffic Motion (FTM) model [15], [16]. Then, under general assumptions on the distribution of inter-vehicle distances, and using standard renewal theory, we obtain the distribution of the number of vehicles that are simultaneously located in the road segment covered by the AP's wireless signal. Such distribution is the keystone of our analytical framework, because it allows us to precisely describe the dynamics of the channel access, and to derive closed-form expressions for various performance metrics, such as network throughput and upload capacity per vehicle.

Key findings and insights of our analysis, which are validated through ns-2 simulations, can be summarized as follows:

- The 802.11 MAC-layer capacity smoothly decreases when increasing the vehicle density. Only under low vehicle densities the average network throughput shows significant variations.
- The total amount of data transferred by a vehicle that drives through the coverage area of a roadside 802.11-based AP according to the CSM model is a monotonically decreasing function of the vehicle density. On the other hand, for vehicles moving according to the FTM model this metric shows a convex-like dependency on the vehicle density[1].
- The ratio between the total amount of data transferred by two vehicles moving with different relative speeds depends on the average speeds of the two vehicles, but it can be independent of the vehicle density[2].

[1]The latter result is also noted in [14].

[2]Proposition 4 derives under which conditions this statement holds.

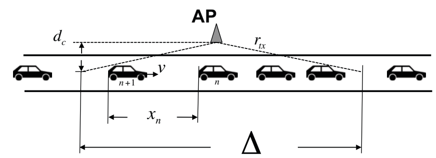

Figure 1. Network topology

As a final remark, we observe that the proposed model can provide the analytical basis to explore enhancements of the standard 802.11 MAC protocol in vehicular environments, as well as to guide the planning and dimensioning of the network roadside infrastructure [17].

The remaining of this paper is organized as follows. In Section II we describe the system model used in our analysis. In Section III, we present the mathematical development of our model. Analytical predictions and simulation results are compared in Section IV. Section V concludes the paper with final remarks.

II. System model

In this study *we consider a single roadside AP deployed along an unidirectional, straight road segment* (for instance a highway segment), as illustrated in Fig. 1. Vehicles are randomly spread along this road segment and they move according to a vehicular mobility model that will be explained later in this section. The vehicles can communicate with the roadside AP only if their distance is below or equal to the maximum transmission range r_{tx}. Thus, the AP's wireless transmissions can cover at most an area of the road segment of length $\Delta = 2 \times \sqrt{r_{tx}^2 - d_c^2}$, where d_c is the distance between the roadside AP and the middle of the road. The nodes share the channel bandwidth using an 802.11-based MAC protocol. Throughout this paper, to simplify the model presentation, we assume ideal channel conditions, i.e., there are not channel errors and hidden terminals, packet capture is not allowed, and the radio transmissions take place at a fixed data rate.

To model vehicular traffic several approaches have been proposed in the literature, and [18] provides a comprehensive survey for the interested reader. In brief, on one end of the spectrum we have traffic stream models that observe the vehicular mobility from a macroscopic point of view. Such models describe the vehicle movements taking into consideration cumulative traffic stream characteristics (e.g., speed, flow density, minimum inter-vehicle distance, etc.) and their relationships to each other. Thus, those models are mainly used to analyse high-level traffic dynamics on separate road segments. On the other end of the spectrum we have microscopic traffic models that consider the movements of each individual vehicle separately, and they characterize a vehicle behaviour through its mobility parameters (e.g., acceleration rate, desired speed, etc.), and the rules of the drivers' behaviours (e.g., car following rules, lane changing rules, etc.). Since in this study we consider uninterrupted traffic flows, traffic stream models are adequate to capture the evolution of the traffic flow under the AP's coverage area.

Let us denote with q the *vehicle intensity*, that is the average number of vehicles that passes a fixed roadside observation point (e.g., the leftmost edge of the AP's coverage area) per unit time. Moreover, let λ be the *vehicle density*, that is the average number of vehicles per unit distance along the road segment. Then, a fundamental relationship in the traffic stream models connects vehicle density and vehicle intensity to the average vehicle speed v as follows [15]:

$$q = \lambda \cdot v \ . \tag{1}$$

In practice, the vehicle density cannot be unlimited due to the physical characteristics of the vehicle (i.e., its length), the road conditions and the safety rules. Thus, let δ_{jam} be the *road capacity* per unit distance, i.e., the minimum allowable inter-vehicle distance. Consequently, the maximum allowable traffic density λ_{jam}, or *jam density*, is given by $\lambda_{jam} = 1/\delta_{jam}$. Typically, in traffic stream models the traffic comes at a complete stop when the jam state is reached. Note that the road capacity (or equivalently the jam density) is a critical parameter in the computation of the average number of contending vehicles under the AP's coverage area, as shown in Section III. In particular, the maximum number of vehicles, say ω_M, that can be accommodated in the AP's coverage area is given by

$$\omega_M = \Delta/\delta_{jam} \ . \tag{2}$$

Different empirical studies provide slightly different estimates, but a reasonable setting is $\lambda_{jam} = 0.12\ veh/m$, which corresponds to $\delta_{jam} = 5\ m$ [13].

To complete the description of the vehicular mobility model, we have to specify the relationship between the vehicle speed and the other system parameters. For the purpose of evaluation, in this study we consider two of the most common mobility models for uninterrupted traffic flows, namely the Fluid Traffic Motion model and the Constant Speed Motion model [18], [19]. We review such models in the following.

- *Fluid Traffic Motion* (*FTM*) model [15]: This is a mobility model that captures the dependency between the speed of a generic vehicle and the average vehicle density in the considered road segment by assuming a linear relationship as follows
$$v(t) = \max\left\{ v_{min}, v_{max}\left(1 - \frac{\lambda}{\lambda_{jam}}\right)\right\} \ , \tag{3}$$
where v_{min} is the minimum allowed/desired speed, and v_{max} is the maximum allowed/desired speed. According to equation (3), when the number of vehicles in the road segment increases all the vehicles slow down (due to the interactions among the vehicles) up to a lower bound on the speed when the vehicle density reaches the jam state.
- *Constant Speed Motion* (*CSM*) model [20]: This is a typical example of stochastic model that sets the speed of all the vehicles in the considered road segment as follows
$$v(t) = v_{min} + (v_{max} - v_{min}) \cdot \eta \ , \tag{4}$$
where η is a uniformly distributed random variable in $[0, 1]$.

In both FTM and CSM models the *vehicle speed is independent of the observation time t, and it is equal for all the vehicles in the same road segment*. This is an important property for our analysis because it implies that: (i) the sojourn time of each vehicle under the AP's coverage area is fixed, and (ii) the inter-vehicle distances maintain substantially constant throughout the traffic flow[3].

As noted previously traffic stream models are commonly used to mimic large-scale traffic phenomena. However, to analyse the impact of different vehicular mobility patterns on the access performance of a roadside AP it is necessary to introduce the concept of *heterogeneous traffic streams*. More precisely, in our work we make the general assumption that there are k_v *different types of vehicles* (e.g., passenger cars, trucks, buses, etc.) in the traffic stream. Without loss of generality, we can assume that the fraction of vehicles of type i ($i = 1, ..., k_v$) within the overall traffic stream is a known value equal to $\alpha^{(i)}$. Intuitively, if λ is the average vehicle density for the whole traffic flow, then the average density of vehicles of type i is given by

$$\lambda^{(i)} = \alpha^{(i)} \cdot \lambda \ . \tag{5}$$

In principle, vehicles of different type may follow different speed models. Nevertheless, for simplicity we assume that all vehicles follows the same speed model (in our case, either FTM or CSM), but with different speed parameters (e.g., minimum and/or maximum allowed speeds). On the other hand, the co-existence in the same road segment of vehicles with different speeds can considerably complicate the analysis because the distance between two consecutive vehicles cannot be assumed constant[4]. To cope with this difficulty, we further extend the description of vehicles' interactions by *adding overtaking capabilities to vehicles*. More precisely, we assume that a vehicle moves to an adjacent lane to overtake the front vehicle if the distance between itself and the front vehicle reduces below δ_{jam}. Then, the vehicle goes back to the previous line as soon as its distance from the overtaken vehicle is higher than δ_{jam}. Without loss of generality, we assume that the change of lines occurs instantly without acceleration and/or deceleration. Such overtaking behaviour guarantees that the road capacity constraint is not violated. Furthermore, it is easy to note that the distance between consecutive vehicles of the same type

[3]This condition guarantees that the distribution of the inter-vehicle distances is not perturbed by the vehicle movements.

[4]For instance, if the front vehicle moves at a lower velocity than the back vehicle, the distance between them reduces as time passes by.

is constant because they move with identical speed. Thus, the analysis of each traffic sub-stream composed of vehicles of the same type is substantially unaffected by the presence of the other traffic sub-streams.

Under the above system model, and assuming that the vehicles operate in *saturated conditions* (i.e., each vehicle has a non-empty transmission buffer when passing through the AP's coverage area) in the following section we model the throughput performance of IEEE 802.11-based V2I communications.

III. Throughput and Fairness Analysis

A. Distribution of the number of contending vehicles under the AP's coverage area

The first step of our analysis is to derive the distribution of the number of contending vehicles under the AP's coverage area. We start by deriving such distribution in the case of an homogeneous vehicular environment with a single vehicle type i. Afterwards, we will generalize our results to an arbitrary number of vehicle types.

Let $\lambda^{(i)}$ be the average number of vehicles that enter the AP's coverage area per unit time (i.e., that pass the leftmost edge of the AP's coverage area per unit time). Then, let $X_n^{(i)}$ denote the distance between the n-th and the $(n+1)$-th vehicle of type i that entered the AP's coverage area. In traffic stream models $\{X_n^{(i)}, n=1,2,...\}$ is typically assumed to be a sequence of non-negative i.i.d. random variables with cumulative distribution function $F^{(i)}(d) = P\{X_n^{(i)} \leq d\}$. Note that the i.i.d. property of the inter-vehicle distances has been also recently confirmed in [21]. Furthermore, previous studies on vehicular mobility traces have indicated that the distance between consecutive vehicles that pass a fixed roadside observation point closely follows an exponential distribution [13], [15]. However, as noted in the previous section, the road-capacity constraint imposes a lower bound on the inter-vehicle distance, say $x_m^{(i)}$. Formally, these features of the $X_n^{(i)}$ r.v. can be analytically described using a *shifted exponential distribution* as follows

$$F^{(i)}(d) = \begin{cases} 1 - e^{-\lambda^{(i)}(d - x_m^{(i)})} & d > x_m^{(i)} \\ 0 & d \leq x_m^{(i)} \end{cases} . \tag{6}$$

Letting $S_n^{(i)} = \sum_{k=0}^{n} X_k^{(i)}$, it follows that S_n represents the distance between the first vehicle and the n-th vehicle that entered the AP's coverage area. Now, the number $N^{(i)}(d)$ of vehicles of type i that are distributed over the first d meters of the AP's coverage area is given by

$$N^{(i)}(d) = sup\{n : S_n^{(i)} \leq d\} . \tag{7}$$

It is well known that, under the assumption that $X_n^{(i)}$ are i.i.d. random variables, the counting process $N^{(i)}(d)$ is a *renewal process*, which is completely defined by the distribution of the distance between vehicles [22]. Specifically, let $F_k^{(i)}(d)$ be the *k-fold convolution* of $F^{(i)}(d)$, defined as

$$F_n^{(i)}(d) = \int_{-\infty}^{d} F_{k-1}^{(i)}(d-y) dF^{(i)}(y) , \tag{8}$$

for $k \geq 1$, while $F_0^{(i)}(d) = F^{(i)}(d)$. Then, the distribution of the renewal process $N^{(i)}(d)$ is given by [22]

$$P\{N^{(i)}(d) = n\} = F_n^{(i)}(d) - F_{n+1}^{(i)}(d) . \tag{9}$$

From the knowledge of the $P\{N^{(i)}(d) = n\}$ distribution, it is straightforward to derive the probability $\pi^{(i)}(n)$ of having n vehicles of type i under the AP's coverage area as follows

$$\pi^{(i)}(n) = P\{N^{(i)}(\Delta) = n\} . \tag{10}$$

However, before deriving a closed form expression for the $P\{N^{(i)}(d) = n\}$ quantity in case of inter-vehicle distances distributed as defined in (6), the following proposition derives the k-fold convolution $F_k^{(i)}(d)$.

Proposition 1: The k-fold convolution of $F^{(i)}(d)$ as defined in (6) for $k \geq 1$ is given by[5]

$$F_k^{(i)}(d) = 1 - \sum_{l=0}^{k} \frac{(\lambda^{(i)})^l}{l!} \left(d - kx_m^{(i)}\right)^l e^{-\lambda^{(i)}\left(d - kx_m^{(i)}\right)} . \tag{11}$$

Proof: Due to space constraints the proof is reported in our technical report [24]. ■

By exploiting Proposition 1, we can now derive the probability $\pi^{(i)}(n)$ as defined in (10). Without loss of generality we assume that $\Delta = \omega^{(i)} x_m^{(i)}$, with $\omega^{(i)} \in \mathbb{N}$. Thus, $\omega^{(i)}$ represents the *maximum* number of vehicles of type i that can be accommodated in the AP's coverage given the minimum inter-vehicle distance constraint $x_m^{(i)}$. The following proposition derive the closed-form expression for $\pi^{(i)}(n)$.

Proposition 2: Under the assumption that the AP's coverage area is $\Delta = \omega^{(i)} x_m^{(i)}$, with $\omega^{(i)} \in \mathbb{N}$, and that the inter-vehicle distance follows the distribution defined in (6), the probability $\pi^{(i)}(n)$ that there are n vehicles of type i under the AP's coverage area is given by

$$\begin{aligned} \pi^{(i)}(n) = & \sum_{k=0}^{n} \frac{(\lambda^{(i)})^k}{k!} \left[(\omega^{(i)} - n - 1)x_m^{(i)}\right]^k e^{-\lambda^{(i)}\left[(\omega^{(i)} - n - 1)x_m^{(i)}\right]} \\ & - \sum_{k=0}^{n-1} \frac{(\lambda^{(i)})^k}{k!} \left[(\omega^{(i)} - n)x_m^{(i)}\right]^k e^{-\lambda^{(i)}\left[(\omega^{(i)} - n)x_m^{(i)}\right]} , \\ & \qquad n < \omega^{(i)} - 1 \end{aligned} \tag{12a}$$

[5]It is worth pointing out that closed-form expressions for the k-fold convolution do not exist for many distributions arising in practice. However, several numerical methods and/or bounds are available for evaluating $F_n(\cdot)$ under general distributions [23].

$$\pi^{(i)}(n) = 1 - \sum_{k=0}^{n-1} \frac{(\lambda^{(i)})^k}{k!} (x_m^{(i)})^k e^{-\lambda^{(i)} x_m^{(i)}} , \qquad n = \omega^{(i)} - 1 \tag{12b}$$

$$\pi^{(i)}(n) = 0 , \qquad n \geq \omega^{(i)} \tag{12c}$$

Proof: Expression (12a) is obtained by substituting (11) in (9). Expression (12b) is obtained by noting that $F_{(n+1)}^{(i)}(d) = 0$ if $d \geq (n+1)x_m^{(i)}$. Similarly, expression (12c) is obtained noting that $F_{(n)}^{(i)}(d) = 0$ if $d \geq n x_m^{(i)}$. ■

So far we have focused on a single type of vehicles. In the remaining of this section we generalize the result of Proposition 2 for the case of multiple types of vehicles. To this end, let $\mathbf{n} = \{n^{(1)}, n^{(2)}, ..., n^{(k_v)}\}$ be a vector, whose component $n^{(i)}$ denotes the number of vehicles of category i in the AP's coverage area, with k_v being the total number of vehicle categories in the system. As before, let $\{X_n^{(i)}, n = 1, 2, ...\}$ be a sequence of non-negative i.i.d. random variables with cumulative distribution function $F^{(i)}(d)$, where $X_n^{(i)}$ denotes the distance between the n-th and the $(n+1)$-th vehicle of type i that entered the AP's coverage area. Furthermore, let us assume that $X_n^{(i)}$ is distributed according to a shifted exponential distribution with parameters $\lambda^{(i)}$ and $x_m^{(i)}$. Finally, let $\overline{\pi}(\mathbf{n})$ be the joint distribution probability that the number of vehicles located under the AP's coverage area is $n^{(1)}$ for vehicles of type 1, $n^{(2)}$ for vehicles of type 2, ..., $n^{(k_v)}$ for vehicles of type k_v. Based on the mobility models and overtaking rules described in Section II, we can conclude that the $X_n^{(1)}, X_n^{(w)}, ..., X_n^{(k_v)}$ are independent processes. Owing to this independency property, we conjecture that it is reasonable to *approximate* the joint probability $\overline{\pi}(\mathbf{n})$ with the product of the probabilities $\pi^{(i)}(n^{(i)})$ of the individual counting processes $N^{(1)}(\Delta), N^{(2)}(\Delta), ..., N^{(k_v)}(\Delta)$. In other words, $\overline{\pi}(\mathbf{n})$ can be computed as follows

$$\overline{\pi}(\mathbf{n}) = \prod_{i=1}^{k_v} \pi^{(i)}(n^{(i)}) \ , \ 0 \leq n^{(i)} \leq \omega^{(i)} , \tag{13}$$

where $\pi^{(i)}(n^{(i)})$ is given by Proposition 2. It is useful to recall that the superimposition of Poisson processes is also a Poisson process. This is not generally true for the superpimposition of arbitrary renewal processes [22]. In other words, we cannot be sure that the renewal property is preserved when renewal processes are added together. However, it is easy to note that the $\pi^{(i)}(n^{(i)})$ distribution closely approximates a Poisson distribution for low vehicle densities (i.e., $\lambda^{(i)} >> 1/x_m^{(i)}$). Thus, we expect that our approximation is accurate, especially in low congested regimes. In following sections we investigate through simulations the accuracy of formula (13).

Now, let us denote with Ω_n the set of all feasible vectors $\mathbf{n}$ such that $n = \sum_{i=1}^{k_v} n^{(i)}$. Formally, we have that

$$\Omega_n = \{\mathbf{n} : \sum_{i=1}^{k_v} n^{(i)} = n, 0 \leq n^{(i)} \leq \omega^{(i)}\} . \tag{14}$$

Using standard probabilistic arguments, the probability $\overline{\pi}_n$ of having n generic vehicles under the AP's coverage area can be calculated as

$$\overline{\pi}_n = \sum_{\mathbf{n} \in \Omega_n} \overline{\pi}(\mathbf{n}) , \tag{15}$$

and the average number of contending vehicles under the AP's coverage area at an arbitrary time is $E[n] = \sum_{n=0}^{\omega_M} \overline{\pi}_n \cdot n$.

To gain a deeper insight into the rationale behind approximation (13), let us introduce the auxiliary random process $\widetilde{X}$ defined as

$$\widetilde{X}_n = \min\{X_n^{(1)}, X_n^{(2)}, ..., X_n^{(k_v)}\} . \tag{16}$$

In other words, $\widetilde{X}$ is a random process representing the minimum of the inter-vehicle distances. Thus, $\widetilde{X}$ can be interpreted as an upper bound for the aggregate vehicle arrival process. The following proposition derives the distribution for the process $\widetilde{X}$

Proposition 3: Under the assumption that $X_n^{(1)}, X_n^{(2)}, ..., X_n^{(k_v)}$ are independent random variables following a shifted exponential distribution (6) with parameters $\lambda^{(1)}, \lambda^{(2)}, ..., \lambda^{(k_v)}$ and $x_m^{(1)}, x_m^{(2)}, ..., x_m^{(k_v)}$, respectively, the $\widetilde{X}_n$ process also follows a shifted exponential distribution with parameters

$$\tilde{\lambda} = \sum_{i=1}^{k_v} \lambda^{(i)} \quad , \quad \tilde{x}_m = \sum_{i=1}^{k_v} \alpha^{(i)} x_m^{(i)} , \tag{17}$$

where $\alpha^{(i)} = \lambda^{(i)}/\tilde{\lambda}$

Proof: Due to space constraints the proof is reported in our technical report [24]. ■

From Proposition 3 it follows that the process $\widetilde{X}$ is stochastically equivalent to a traffic stream with overall arrival rate equal to the weighted sum of the arrival rates of the individual traffic sub-streams $X_n^{(i)}$.

B. Network and per-vehicle performance

Our analysis is developed under the following simplifying assumptions:

- **A1**: There are not association and synchronization delays between the vehicles and the roadside AP.
- **A2**: The frame service time is shorter than the inter-time between arrivals/departures of vehicles into/from the AP's coverage area. This implies that the number of contending vehicles is constant during the frame transmission[6].

[6]Note that the frame transmission time is of the order of a few milliseconds, thus this approximation is reasonable.

A3: To compute the transmission probability of a generic vehicle we use the *decoupling approximation* as in [9]–[11]. More precisely, let τ_n be the probability that a vehicle transmits a packet at the beginning of an empty time slot under the assumption that there are other $(n-1)$ vehicles contending for the channel access. Then, τ_n is a function of the backoff parameters and the n value, but it does not depend on the state of the other contending vehicles.

Under assumption A3 above, several authors have independently derived the expression of τ_n for the 802.11-based backoff mechanism under saturation conditions. In our analysis, we use the expression given in [11], which jointly accounts for the maximum retransmission limit and the maximum contention window size:

$$\tau_n = \frac{2q_n(1-p_n^{r+1})}{q_n(1-p_n^{r+1})+CW_0[1-p_n-p(2p_n)^m(1+p_n^{r-m}q_n)]} , \tag{18}$$

where

$$p_n = 1-(1-p_n)^{n-1} \tag{19}$$

is the conditional collision probability, $q_n = 1 - 2p_n$, CW_0 is the minimum contention window, r is the maximum retry limit, and m is the number of retransmissions at which the contention window reaches its maximum value $(m \leq r)$[7]. For instance, following the IEEE 802.11a/b/g standard, we have that $CW_0 = 32$ slots, $m = 5$ and $r = 7$.

Let S_n be the *average network throughput given n contending vehicles*, i.e., the total amount of data transferred by the moving vehicles to the roadside AP per unit time conditioned to having n vehicles in the AP's coverage area. It is a well-established result that, once the τ_n value is known, the saturation throughput for 802.11-based networks can be computed as [25], [26]

$$S_n = \frac{\tau_n^s \tau_n^{tr} E[P]}{(1-\tau_n^{tr})\sigma + \tau_n^s \tau_n^{tr} T_s + (1-\tau_n^s)\tau_n^{tr} T_c} , \tag{20}$$

where $\tau_n^{tr} = 1 - (1-\tau_n)^n$ is the probability that a generic slot is not idle, $\tau_n^s = n\tau_n(1-\tau_n)^{n-1}/\tau_n^{tr}$ is the probability that a transmission is successful, $1-\tau_n^s$ is the probability of collision, $E[P]$ is the average payload size, T_s and T_c are the average duration, including MAC overheads, of a successful transmission and a collision, respectively. Then, the overall network throughput can be straightforwardly computed as

$$E[S] = \frac{\sum_{n=1}^{\omega_M} \overline{\pi}_n \cdot S_n}{1-\overline{\pi}_0} , \tag{21}$$

where ω_M is the maximum capacity of the road segment covered by the AP's wireless signal as defined in (2), namely, $\omega_M = \Delta/\delta_{jam}$, and $1 - \overline{\pi}_0$ is the normalization factor needed to take into account that S_n is conditioned to have at least a vehicle in the AP's coverage area (i.e., $n > 0$).

To evaluate the service level that can be provided to individual vehicles, it is useful to quantify the total amount of data that a vehicle can transfer to the roadside AP when driving through the AP's coverage area. The vehicular mobility model comes into play in the computation of such metric, because the total amount of data transferred by a vehicle must be a function of the vehicle's sojourn time under the AP's coverage area. More precisely, let $\gamma_n^{(i)}$ be the overall amount of data transferred by a vehicle of type i when driving through the AP's coverage area, given that the total number of contending vehicles is n. To derive $\gamma_n^{(i)}$ it is useful to introduce s_n, defined as the *average throughput per vehicle* given that there are n contending vehicles under the AP's coverage area. Under the assumption that all the vehicles use the same backoff parameters, it holds that the vehicles have the same number of opportunities per unit time to access the wireless channel [11]. Given the fair sharing of transmission attempts, it holds that $s_n = S_n/n$. It is now straightforward to obtain that $\gamma_n^{(i)} = s_n \cdot \mu^{(i)}$, where $\mu^{(i)}$ is the *average sojourn time* under the AP's coverage area for vehicles of type i. More precisely, let $\overline{v}^{(i)}$ be the average speed for vehicles of type i. Then, $\mu^{(i)}$ can be computed as

$$\mu^{(i)} = \frac{\Delta}{\overline{v}^{(i)}} . \tag{22}$$

It is easy to observe that for the FTM model, $\overline{v}^{(i)}$ is given directly by formula (3), while for the CSM model it holds that $\overline{v}^{(i)} = (v_{max}^{(i)} + v_{min}^{(i)})/2$. Now, the overall amount of data transferred by a vehicle of type i is given by

$$E[\gamma^{(i)}] = \frac{\sum_{n=1}^{\omega_M} \sum_{\mathbf{n} \in \Omega_n} \pi^{(i)}(n^{(i)}) \cdot s_n \cdot \mu^{(i)}}{1-\overline{\pi}_0} , \tag{23}$$

where $n^{(i)}$ is the i-th component of vector $\mathbf{n}$.

Finally, an important performance metric for the vehicular environment under investigation is the *fairness* in terms of equality of the uploaded data per vehicle. We have previously observed that the 802.11 DCF access scheme is intrinsically fair from the point of view of channel access opportunities and throughput performance. However, this does not imply that all vehicles, irrespective of their mobility characteristics, are able to upload the same amount of data when driving through the AP's coverage area. To characterize the impact of the vehicular mobility model on the system fairness, we introduce the *normalized upload capacity* $r^{(i)}$ for type-i vehicles as follows

$$r^{(i)} = \frac{E[\gamma^{(i)}]}{\sum_{j=1}^{k_v} E[\gamma^{(j)}]} . \tag{24}$$

Intuitively, formula (24) quantifies the fraction of channel resources that each vehicle of type i is able to "consume"

[7]Note that (18) and (19) represent a non linear system in the two unknowns τ_n and p_n, which can be efficiently solved using standard numerical techniques.

during its connection with the AP. Note that $\sum_{i=1}^{k_v} r^{(i)} = 1$. The following proposition derives a simple closed-form expression for the $r^{(i)}$ quantity in the special case of equally distributed traffic sub-streams.

Proposition 4: In the case that $\pi^{(i)}(n^{(i)}) = \pi^{(j)}(n^{(j)})$ for $n^{(i)} = n^{(j)}, i \neq j$, it holds that

$$r^{(i)} = \prod_{\substack{k=1\\k\neq i}}^{k_v} \overline{v}^{(k)} \Bigg/ \sum_{j=1}^{k_v} \prod_{\substack{k=1\\k\neq j}}^{k_v} \overline{v}^{(k)} \; . \qquad (25)$$

Proof: Formula (25) is straightforwardly obtained after standard algebraic manipulations by substituting expression (22) into (23), and noting that $E[\gamma^{(i)}]$ reduces to $c/\overline{v}^{(i)}$, where c is a constant independent of i . ■

Proposition 4 points out that, under equally distributed traffic sub-streams, the normalized upload capacity per vehicle is independent of the vehicle density, and it depends only on the average relative speeds of vehicles. Such unexpected result will be validated through simulations. Finally, in the case that all the vehicles move with the same average speed $\overline{v}$, Formula (25) simplifies to

$$r^{(i)} = \frac{(k_v - 1)\overline{v}}{k_v(k_v - 1)\overline{v}} = \frac{1}{k_v} \; , \qquad (26)$$

which implies that the system is fair, because each category of vehicles can upload the same amount of data during its sojourn time in the AP's coverage area.

IV. Model Validation

To validate our analytical model, we have conducted a wide range of simulations using the ns-2.34 simulator. In the following, we first describe the simulation setup. Afterwards, we compare the analytical and simulation results for the performance metrics defined in Section III.

A. Simulation setup

We simulate a two-lane unidirectional, straight road segment of length Δ. One lane is the main lane for the traffic flow, while the adjacent lane is used only for the overtaking of slower front vehicles, as explained in Section II. A fixed roadside AP is located along the road at a distance d_c from the middle of the road. Vehicles enter/leave the system from the borders of the topology, and inter-vehicle distances are distributed according to the shifted exponential distribution defined in (6). The road capacity is $\lambda_{jam} = 0.12 \; veh/m$ [13].

Vehicles compete for the channel access using IEEE 802.11 DCF with RTS/CTS disabled. Unless otherwise stated, the packet payload size is constant and equal to 1000 bytes, and the data transmission rate is fixed and set to 11 Mbps. For the purpose of evaluation, we consider default 802.11b MAC and PHY parameters as used in ns-2, however the same methodology can be applied to the IEEE 802.11p/WAVE standard. Finally, the AP's coverage area Δ is computed as $\Delta = 2 \times \sqrt{r_{tx}^2 - d_c^2}$. In our simulations $d_c = 50$ m and the largest Δ we have considered is $\Delta = 500$ m. This Δ value corresponds to a transmission range of about 255 meters using the free-space propagation model, which is in line with the ranges observed in field measurements [1], [5], [6].

Table I
Parameter Settings for Mobility Models and Vehicle Categories.

Model	Scenario	Veh. Type i	Mobility parameters		
			$v_{max}^{(i)}$ $[m/s]$	$v_{min}^{(i)}$ $[m/s]$	$x_m^{(i)}$ $[m]$
CSM	$K1$	1	25	5	5
	$K2$	1	25	5	5
		2	18.75	5	5
FTM	$K1$	1	25	0	5
	$K2$	1	25	0	5
		2	18.75	0	5

The parameter settings used in the simulations for the CSM and FTM models are reported in Tab. I. The selected parameters are derived from real-world values, as observed in [19]. In the following tests, we have considered two vehicular network scenarios. The first scenario, which is denoted by $K1$, involves a single category of vehicles, and it is used to validate our analysis in homogeneous mobility conditions. The second scenario, which is denoted by $K2$, involves two categories of vehicles, where type-2 vehicles have a maximum speed that is 75% of the maximum speed of type-1 vehicles (see Tab. I for the exact values). This second case is used to validate our analysis in heterogeneous mobility conditions. Due to space limitations we do not show results with a larger number of vehicle types and/or more variegated mobility conditions. However, the observed behaviours would be relatively similar.

All following simulations use a 2000-seconds warm-up period and all the quantities of interest are measured over the next 18000 seconds, which corresponds to five hours of simulated vehicular mobility. Note that a sufficiently long simulation duration is necessary to converge to steady-state regimes, especially in highly congested scenarios. Confidence intervals at 95% are estimated by replicating ten times each simulation run with different random seeds.

B. Roads with one type of vehicles

First of all, we evaluate the ability of our model to correctly characterize the number of contending vehicles under the AP's coverage area, both in terms of average values and distribution functions. To this end, Fig. 2 shows the average number of contending vehicles under the AP's coverage area as predicted by our analysis and measured in the simulations versus the vehicle density. The maximum vehicle density we have tested is 0.12 veh/m, because this corresponds to the limiting road capacity. The shown results are obtained for $\Delta = 500$ meters and $\Delta = 350$ meters. The plots demonstrate that our model captures with remarkably precision the average number of contending vehicles under the AP's

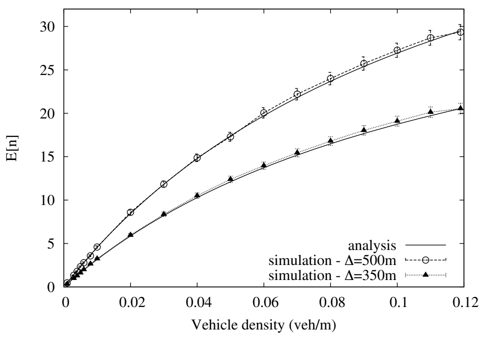

Figure 2. Scenario $K1$ – Average number of contending vehicles under the AP's coverage area vs. vehicle density: analysis and simulation.

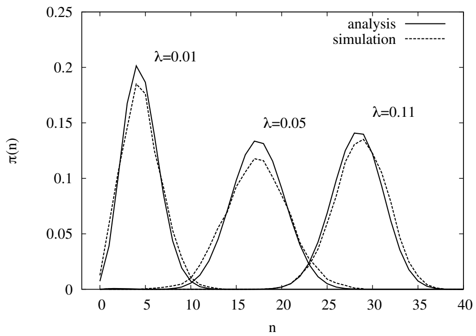

Figure 3. Scenario $K1$ – $\overline{\pi}(n)$ distribution for three representative vehicle densities and $\Delta = 500$ m: analysis and simulation.

coverage area, correctly taking into account the impact of road capacity constraint on this metric. Intuitively, when compared with $\Delta = 500$ m, an AP's coverage area of 350 m presents a fewer number of contending vehicles. A second important finding is that this metric does not depend on the considered speed model[8] but only on the distribution of inter-vehicle distances. Note that the results shown in Fig. 2 have been obtained using the FTM model, whereas results for the CSM model are not reported in the graphs because they are practically overlapping. To gain a deeper insight in the average behaviours shown in Fig. 2, Fig. 3 depicts the distribution of the number of contending vehicles under the AP's coverage area as derived from the simulation traces and formula (10), for low, mid and high vehicle densities, in the case $\Delta = 500$ m. The figure shows that the model predictions match very well the simulation results independently of the vehicle density.

In the following we verify the ability of our model to correctly estimate both aggregate and per-vehicle throughput performance. To this end, in Fig. 4 we report the network throughput $E[S]$ estimated by our formula (21) and obtained in the simulations for $\Delta = 500$ meters and $\Delta = 350$ meters, assuming that the vehicles move according to the FTM model. For the sake of clarity, since the curves for the

[8]Note that this conclusion is valid for constant-speed mobility models, such as CSM and FTM models. We believe that alternative speed models, such as car-following models, may induce more complex behaviours for the $E[n]$ metric.

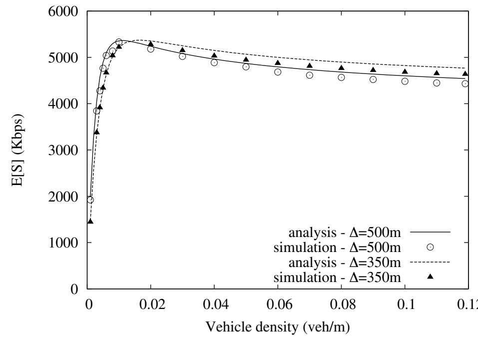

Figure 4. Scenario $K1$ – Network throughput vs. vehicle density: analysis and simulation.

considered Δ values are very close to each other, the confidence intervals are not reported, but they are tight. The plots indicate that the analysis can reasonably well approximate the observed network throughput. The slight throughput overestimation provided by the analysis can be explained by noting that formula (20) would be valid only in stationary regimes. However, a moving vehicle entering the AP's coverage area will take some time before reaching a steady state behaviour, and our model cannot capture such transient conditions. Nevertheless, the impact of transient behaviours on the throughput performance appears limited and it does not significantly affect the accuracy of our analytical model. Moreover, from the shown results we can observe that at very low vehicle densities (in our case $\lambda < 0.005$) the network throughput is quite low. This can be explained by noting that at those vehicle densities the average number of vehicles under the AP's coverage area is as low as 1 or 2 stations. It is well known that the throughput of the 802.11 DCF access method highly depends on the value of the minimum contention window (32 slots for 802.11a/b/g standard), which may penalize the throughput in the case of small number of contending stations [9]. Another interesting result is that there is a region around low vehicle densities where the network throughput is maximized. Then, if we increase the vehicle density beyond this optimal value, the network throughput start degrading because the number of vehicles in the AP's coverage area increases as well; thus, the channel becomes more congested and the higher number of collisions among vehicles reduces the MAC protocol efficiency. However, the throughput degradation is quite smooth, and even when the vehicle density approaches the jam density, the network throughput is still reasonably good. Finally, when compared with $\Delta = 500$ m, the MAC-layer capacity with $\Delta = 350$ m is smaller for low vehicles densities and bigger in the other cases. This suggests that the optimal network performance depends on both vehicle density and AP's coverage range.

Fig. 5 shows the analytical and simulation results for the total amount of data transferred by a vehicle that drives through the AP's coverage according to the CSM model or the FTM model, versus the vehicle density. From Fig. 5,

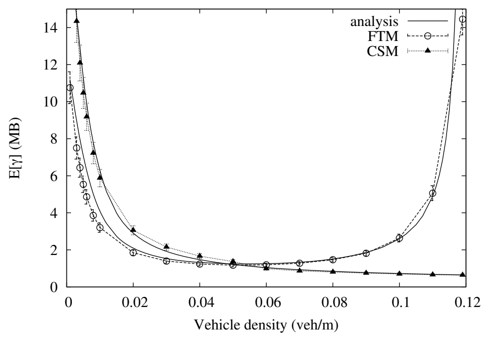

Figure 5. Scenario $K1$ – Total amount of data transferred by a vehicle vs. vehicle density for $\Delta = 500$ m: analysis and simulation.

we draw the two following interesting observations. First, when vehicles move according to the CSM model, $E[\gamma]$ is a monotonically decreasing function of the vehicle density. This can be explained by noting that, under the CSM model, the vehicle's sojourn time is independent of the vehicle density. On the other hand, in most situations the higher the vehicle density, the lower the average throughput per vehicle [9]. Thus, the vehicle can transfer to the AP a lower amount of data if we increase the vehicle density. Secondly, when vehicles move according to the FTM model, the amount of data they are able to transfer to the AP when passing through the AP's coverage area is a complex function of the vehicle density, with a convex-like and symmetrical shape. In particular, when the vehicle density is low, the vehicle speed approaches its maximum and the sojourn time is minimum. However, the average number of contending vehicles under the AP's coverage area is also very small and they are able to transmit very fast to the AP. This explains the large amount of uploaded data per vehicle. As the vehicle density increases, the vehicle speed decreases and the duration of the vehicle sojourn time increases as well. However, this increase is balanced by the increase in the channel contention level, which substantially reduces the throughput per vehicle. For these reasons there is a large operating region where the total amount of data transferred by a vehicle is mostly constant. Finally, when the vehicle density approaches the jam density, the vehicles gradually stop and the very long (asymptotically infinite) sojourn time dominates over the throughput reduction. This explains the new rapid increase in the amount of data transferred by each vehicle.

C. Roads with two types of vehicles

In this section we validate our analytical model in the case of vehicular environments with two categories of vehicles. To avoid any bias between the two traffic sub-streams and to better highlight eventual unfairness problems, all the results shown in the following are obtained in the case $\lambda^{(1)} = \lambda^{(2)}$ (i.e., $\alpha^{(1)} = \alpha^{(2)} = 0.5$). In other words, in the overall traffic flow vehicles of type 1 and vehicles of type 2 are *equally* distributed (i.e., $\pi^{(1)}(n^{(1)}) = \pi^{(2)}(n^{(2)})$ for $n^{(1)} = n^{(2)}$). The other mobility parameters used in the simulations are listed in Tab. I. For the sake of figure clarity, we report only results for $\Delta = 500$ meters.

[9]The only exception to this behaviour is for a small operating region at very low vehicle densities, as shown in Fig. 4

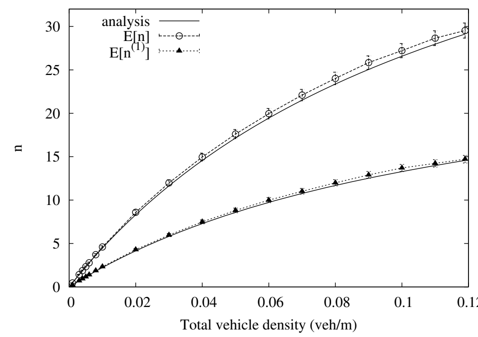

Figure 6. Scenario $K2$ – Average number of contending vehicles under the AP's coverage area versus the total vehicle density: analysis and simulation.

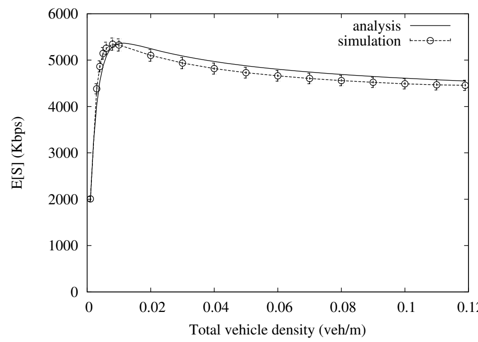

Figure 7. Scenario $K2$ – Network throughput vs. total vehicle density: analysis and simulation.

Fig. 6 shows the average total number of vehicles and the average number of type-1 vehicles under the AP's coverage area as predicted by our analysis and measured in the simulation tests, versus the total vehicle density $\lambda = \lambda^{(1)} + \lambda^{(2)}$. The shown results demonstrate that our model can describe with high accuracy the average contention levels in the AP's coverage area. Moreover, since $\lambda^{(1)} = \lambda^{(2)}$, type-1 and type-2 vehicles contribute equally to the contention in the AP's coverage area. Note that the results shown in Fig. 6 have been obtained using the FTM model, whereas results for the CSM model are not reported in the graphs because they are practically overlapping. Due to space limitations we do not report figures on the distribution $\overline{\pi}(\mathbf{n})$, which also confirm the behaviours shown in Fig. 3.

Fig. 7 shows the average network throughput versus the total vehicle density. Interestingly, we can observe a performance trend very similar to the one shown in Fig. 4. This confirms that the MAC-layer capacity mainly depends on the total number of vehicles that simultaneously contend for the channel access and it is not affected by the differences in the relative speed of the vehicles. We do not report figures on the $E[\gamma^{(i)}]$ values because the trend of the plots are qualitatively the same as in Fig. 5, and we prefer to focus on

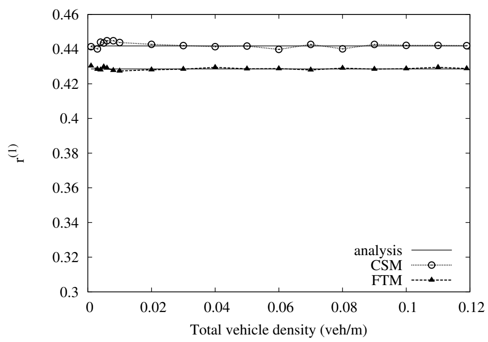

Figure 8. Scenario $K2$ – Normalized capacity of type-1 vehicles vs. total vehicle density: analysis and simulation.

the more interesting results related to system fairness. To this end, Fig. 8 shows the normalized upload capacity $r^{(1)}$ versus the total vehicle density for both CSM and FTM models. Note that $r^{(2)} = 1 - r^{(1)}$, thus it is not reported in the figure. The shown results confirm the findings of Proposition 4, i.e., that the normalized upload capacity does not depend on the vehicle density under the condition that vehicles of type 1 and vehicles of type 2 are equally distributed in the overall traffic flow. Furthermore, using formula (25) and the values reported in Tab I, it is easy to derive that $r^{(1)}_{FSM} \approx 0.428$ and that $r^{(1)}_{CSM} \approx 0.441$. Such analytical predictions are in very good accordance with the results shown in Fig. 8. Finally, it is worth mentioning that knowing the fairness properties of the system, and how they depend on the vehicular parameters, the AP could manipulate the backoff parameters used by different categories of vehicles to enforce fairness. We leave the design of such adaptive strategies for our future work.

V. Conclusions

In this paper, we have proposed a new model to evaluate the throughput performance of multiple vehicles sharing the wireless resources of one 802.11-based AP in a given mobility scenario. Our model is able to precisely capture the impact of road capacity, vehicle density, and differences in the relative speed of vehicles on the throughput performance of V2I communications. Some key findings from our results are that: (i) the MAC-layer capacity smoothly degrades increasing the vehicle density, and (ii) heterogeneous vehicular environments may suffer from unfairness. Our future work will focus on extending this analytical framework towards three main directions: $1)$ range-dependent packet loss rates, $2)$ bursty traffic sources, and $3)$ car-following traffic models. Furthermore, we will investigate how to exploit our model to optimally adapt the 802.11 MAC parameters to vehicular mobility patterns.

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