Exploiting Interference for Capacity Improvement in Software-Defined Vehicular Networks

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\section*{ABSTRACT} Vehicular ad hoc networks (VANETs), which are deployed along roads, make traffic systems safer and more efficient. The existing theoretical results on capacity scaling laws provide insights and guidance for designing and deploying VANETs. As a new paradigm of VANETs, software-defined vehicular ad hoc networks (SDVANETs) separate the data plane from the control plane. For many prospective applications, software-defined technology will be used in VANETs to achieve some general targets, such as network management. Therefore, a capacity analysis is critical and necessary for SDVANETs. In this paper, we propose a new fundamental framework named real vehicular wireless network model (RVWNM), which enables a more realistic capacity analysis in SDVANETs. We first introduce a Euclidean planar graph that can be constructed from any real map of an urban area and that represents the practical geometry structure of the urban area. Then, an interference relationship graph is abstracted from the Euclidean planar graph, which considers the transmission interference relations among the nodes in the network. Finally, we theoretically analyze the interference relationships in the interference relationship graph. A practical geometrical structure is used to calculate the asymptotic capacity of SDVANETs. To verify the feasibility of RVWMN, we calculate the asymptotic capacity of social-proximity urban networks. We also consider the social-proximity-based mobility of vehicles, and we derive asymptotic capacity bounds for sparse SDVANETs and constant bounds for high-density SDVANETs.

\section*{INDEX TERMS} Software-defined vehicular ad hoc networks (SDVANETs), interference, capacity scaling law, graph theory, independent set.

\section*{I. INTRODUCTION} Vehicular ad hoc networks (VANETs) can provide safety and traffic information for both drivers and network managers without using a wired backbone. Thus, a VANET not only makes transportation systems safer and more efficient but also works as a good platform for cloud computing [1]–[3]. VANETs have many critical problems, such as privacy [4]–[6], security [7], coverage [8] and capacity [9], [10]. Capacity, as an important and fundamental property of VANETs, ad hoc networks and wireless sensor networks [11]–[14], is critical for theoretical analysis. Moreover, capacity provides guidelines for the deployment of ad hoc networks. However, determining the capacity of distributed wireless networks is one of the most general but challenging problems. The existing techniques from information theory cannot efficiently address this problem. Thus, some probability and statistical methods have been proposed to analyze and calculate the capacity of ad hoc networks [9]. These technologies have led to rapid progress in studying capacity under various scenarios over the past decade.

Software-defined networking was recently introduced in VANETs to enhance performance by separating the control plane and the data plane. This new paradigm, software-defined vehicular ad hoc networks (SDVANETs), controls the entire network in a centralized manner, thus making SDVANETs more efficient than standard VANETs.

However, three unique properties of SDVANETs make analysis using probability and statistical techniques in
SDVANETs difficult. These properties can be summarized as follows.

- Since all vehicles can only move along roads, the layout of roads in an urban area directly affects the capacity of the SDVANETs.
- Since the geometries of the roads in different urban areas are different, we cannot use a universal model for all urban areas.
- Since vehicles move neither randomly nor completely regularly, their mobility is characterized in a statistical manner.

To solve the above problem, we propose a new fundamental framework named RVWNM (real vehicular wireless network model) that is constructed using a Euclidean planar graph and an interference relationship graph. RVWNM is a real construction of vehicular networks because it is abstracted from a real-world map and has all the geometrical properties of a real-world map. In addition, using methods in graph theory to analyze the RVWNM is convenient. The interference relationship graph is obtained through abstracting the Euclidean planar graph, which will be introduced in Section III. To schedule the interference in the MAC layer of wireless transmission, we use the protocol interference mode in [16]–[18] as our interference model.

Under the RVWNM, we develop a theoretical analysis on the throughput capacity limits of the urban social-proximity SDVANET to achieve $\Theta(1/n)$ in sparse areas and constant capacity bounds in high-density areas using a two-hop relay scheme [19], where $n$ denotes the number of vehicles. The following is a summary of our contributions:

- We propose a new framework named RVWNM that is constructed using a Euclidean planar graph and an interference relationship graph. The Euclidean planar graph can be abstracted from the real map of any urban area. In contrast to the general and inaccurate results obtained under the general grid-like construction, which neglects the non-uniformity of urban roads and the difference between different urban areas, the asymptomatic capacity obtained under this framework is targeted and precise.
- We abstract the Euclidean planar graph from a Euclidean planar graph based on the interference between units. We introduce the independent set from graph theory to demonstrate the interference relationships between units. The independent set makes the analysis and calculation of concurrent transmission flows easier, which is important for calculating asymptotic capacity.
- For the precise asymptotic capacity, we must consider the social-proximity movement of the vehicles. We find it unnecessary to model the trajectory of every vehicle; thus, we use localized movement to model the action of the vehicles. Let each vehicle independent and identically distributed (i.i.d.) select one unit as its center of localized movement, and we refer to it as the home-point. The spatial stationary distribution of vehicles decays as a power law of an exponent with the distance from the home-point.
- To verify the feasibility of the proposed method, we calculate the asymptotic capacity of two-hop vehicular networks using the protocol interference model.

In 2007, Pishro-Nik et al. [9] proposed a grid-like construction to illustrate all the roads in an urban area, as shown in Fig. 1. Every line in this construction denotes a road, and the $m$ vertical lines intersect with the $m$ horizontal lines, which compose a grid-like construction. In 2012, Lu et al. [15] extended the work of Pishro-Nik et al. and obtained an almost constant per-vehicle throughput in a high-density scenario. As shown in Fig. 2, different areas of an urban region have different road densities, and the shapes of the areas surrounded by the roads differ even more significantly. Therefore, if we use a normalized gird-like construction to model an urban area, we cannot obtain a precise and suitable asymptotic capacity.

FIGURE 1. The grid-like structure denotes the roads of an urban area.

FIGURE 2. The real map of an urban area obtained from Helsinki.
capacity in the sparse area is bounded by $\Theta(1/n)$.

We also calculate the average capacity of SDVANETs.

To the best of our knowledge, this is the first framework that offers a targeted and precise asymptotic capacity, which differs from the normalized grid-like construction. This framework can also be used to calculate asymptotic capacity under other scenarios with different interference models or different routing schemes.

The remainder of this paper is organized as follows. Section II reviews related works. Section III introduces the network model, definitions of capacity and known theorems used in the proof. Section IV first introduces the RVWNM and then calculates the capacity of SDVANETs. Section V discusses the limitations of this paper. Section VI concludes the paper with future works.

II. RELATED WORK

In 2000, Gupta and Kumar initially investigated the throughput capacity of wireless networks [16], where it was shown that the throughput $\lambda(n)$ obtainable by each node for a randomly chosen destination is $\Theta\left(\frac{W}{\sqrt{n \log n}}\right)$ bits per second under a non-interference protocol, and the throughput is only $\Theta\left(\frac{W}{\sqrt{n}}\right)$ bits per second under optimal conditions. Following the seminal work of Gupta and Kumar, theoretical studies of fundamental scaling laws and fundamental capacity limits have attracted more attention from researchers. One of the topics is extending the original work performed by Gupta and Kumar. This topic includes complete proofs on unicast [20] and extends the work to the case of multicast [21] and broadcast [22]. Another topic is the trade-off between capacity and other network variables. In 2002, Grossglauser and Tse found that the per-node throughput can increase dramatically when nodes are mobile rather than fixed [23]. However, the end-to-end delay is very large when we introduce mobility in the network. Thus, some researchers are focusing on the capacity-delay trade-off [24] and the capacity of energy-constrained networks [25]. Third, other works attempt to change the classical ad hoc network model, which is called the random homogeneous model. This line of work includes studies of arbitrary networks [26], inhomogeneous networks [27], hybrid networks [28], allowing nodes to cooperate with a hierarchical MIMO network [29] and using network coding [30], [31] and MPR [32] to improve the network capacity.

The study of capacity for vehicular ad hoc networks developed slowly until 2007, when Pishro-Nik and Ganz first initiated the study of capacity for VANETs and provided a general grid-like construction [9]. Every line in the construction denotes a road, and the $m$ vertical lines intersect with the $n$ horizontal lines, which compose a grid-like construction. The need for a new capacity metric was discussed in their work. They showed how the road geometry affects the capacity, and they calculated the capacity for different road structures. They also showed that the sparseness condition could obtain a better capacity; conversely, if the sparseness condition does not hold, then the transport capacity of VANETs can be as large as $\Theta\left(\frac{1}{n \ln n}\right)$. The grid-like structure as a general network model framework makes the study of capacity limits easy and convenient. Lu et al. [15] used the structure representing urban VANETs. They investigated the case of $n$ vehicles on grid-like streets while the density of vehicles is fixed. The number of roads increases linearly with the population of vehicles. In their work, almost constant per-vehicle throughput $\Omega(1/\log(n))$ and almost constant delay $O(\log^2(n))$ are achievable with high probability. They also obtained the trade-off between delay and capacity $O(\log^3(n))$.

The localized mobility of vehicles is the main characteristic of social-proximity urban vehicular ad hoc networks. The steady-state location probability of vehicles was generally modeled to exponentially decay as a power law function [33]. The model is validated in [34] through a real-world trace. Alfano et al. [27] considered the situation in which each node moves around its own home-point according to a restricted mobility process. The spatial stationary distribution of nodes decays as a power law of exponent $\delta$ with the distance from the home-point. They analyzed the delay-throughput scaling trade-off for different values of $\delta$. In particular, they showed that for $\delta = 2$, it is possible to achieve almost constant delay and almost constant per-node throughput.

III. NETWORK MODEL

To obtain the Euclidean planar graph of RVWNM, we define the disk centered at the intersection in a real map with diameter $r$ as a unit disk, where $r$ is the transmission range. The transmission range of wireless communication equipment is approximately 300 meters; thus, a road between two intersections that is 300 meters could be covered by units. Note that the length between two intersections of most roads is less than 300 meters, and vehicles typically pass through the middle of the roads at high speed. Thus, we can neglect occasional cases when the vehicle is not under coverage. Units in the real-world map are denoted by vertices on the Euclidean planar graph according to their coordinates in the real-world map. If there is a road between two units, then we place an edge between the two corresponding vertices.

For an arbitrary real-world area, we can obtain an arbitrary RVWNM through abstraction. For the general theoretical asymptotic capacity, we assume that the overall area is $S$ and the perimeter is $L$. We consider units to be randomly distributed in the area, and the connection between every two adjacent units is random. We abstract the above network area to derive a random RVWNM.

The grid-like network geometry is convenient because of its partially normalized structure. To derive a more precise theoretical capacity under a real scene, we propose a novel network model that is constructed by a Euclidean planar graph and an interference relationship graph. Then, we introduce the process of constructing the model from a real-world map.

Given a real-world map (Fig. 2), we treat every intersection as a center and draw a circle with diameter $r$. The road
covered by a circle is a unit. All units compose a unit set \( U = \{u_1, u_2, \cdots, u_N\} \). Units in the real-world map are denoted by vertices on the Euclidean planar graph according to their coordinates in the real-world map. Place \( U \) on \( G_R \) according to the coordinates of units, and place an edge between every two units that are connected in the real-world map. Thus, we derived an arbitrary Euclidean planar graph \( G_E \).

**FIGURE 3.** A random Euclidean planar graph.

To obtain theoretical results, we randomly choose a region \( G_R \) with perimeter \( L \). For simplicity, we use the derived Euclidean planar graph \( G_R \) as a random Euclidean planar graph, as shown in Fig. 3. In Fig. 3, all units denoted by a vertex compose the set \( U_R = \{u_1, u_2, \cdots, u_{N_p}\} \), where \( N_p \) is the number of units in \( G_R \).

We introduce different calculation methods for an arbitrary network geometry and a random network geometry.

**FIGURE 4.** Examples of inhomogeneous distributions of vehicles.

Since vehicles move in a localized region, the density of vehicles in the network is inhomogeneous, as shown in Fig. 4. We use a probability density function to represent the inhomogeneous density of vehicles in the following content.

A. MOBILITY MODEL

In ad hoc networks, to simplify the calculation of asymptotic capacity, the i.i.d. mobility model is widely used. However, the traffic of SDVANETs is not a random event; rather, it has social-proximity property. Therefore, we employ the restricted mobility model to represent the social-proximity traffic of SDVANETs. In the Euclidean planar graph \( G_R \) that we derived above, vehicles move between units. Since vehicles move in a localized region centered at a fixed home-point because of social activities, each vehicle uniformly chooses a unit in \( G_R \) as its home-point. We combine close home-points to make the covered areas of home-points have little overlap with each other. We call the area covered by a home-point a sub-area.

Let \( X_i(t) \) denote the location of vehicle \( i \) at time \( t \) and \( X_i^h(t) \) denote the location of the home-point of vehicle \( i \) at time \( t \), where \( t \) is an integer that denotes the slot sequence number. The Euclidean distance between vehicle \( i \) and its home-point at time \( t \) is defined by \( d_i \), i.e., \( d_i = \| X_i(t) - X_i^h(t) \| \). The spatial stationary distribution of nodes can be described by a generic, non-increasing function \( \phi(d) \) in terms of the distance \( d \) from the home-point, and we assume that \( \phi(d) \) decays as a power law of exponent \( \delta \), i.e., \( \phi(d) \sim d^{-\delta} \) with \( \delta > 0 \) as in paper [33].

We denote a function \( s(d) = \min(1, d^{-\delta}) \) and normalize it to derive a probability density function over the network area \( \phi(d) = \frac{s(d)}{\int s(d) \, \mathrm{d}d} \), where \( \delta > 0 \) denotes a uniform distribution over the space. We obtain the same behavior as that of a static network if we let \( \delta \) be infinity. The value of \( \delta \) is analyzed in [33].

B. COMMUNICATION AND INTERFERENCE MODEL

Assume that we can only transmit one packet during a time slot. Due to the interference of wireless transmission, a vehicle cannot transmit with more than one vehicle during the same time slot. To schedule transmission flows, we adopt the protocol interference model introduced in [16], which roughly represents the behavior of a wireless MAC protocol. The protocol interference model schedule is defined as follows.

At each time slot, a transmission from vehicle \( i \) to vehicle \( j \) is successful only if 1) \( \| X_i(t) - X_j(t) \| \leq r \), and 2) for any other vehicle \( l \) that transmits at \( t \), \( \| X_l(t) - X_j(t) \| \geq (1 + \Delta)r \), where \( \Delta \) is a guard factor that defines a protection zone around the receivers.

To clearly define the interference between units, an interference relationship graph \( G_P \) is constructed through neglecting the geometry of Euclidean planar graph \( G_R \). In \( G_P \), we also use a vertex to denote the unit. In contrast to Euclidean planar graph \( G_R \), the edge in \( G_P \) between unit \( i \) and unit \( j \) represents the distance \( d_{ij} \) between them. They cannot
transmit packets during the same time slot. We introduce the interference relationship graph in detail in Section IV.

C. TRANSMISSION MODEL AND RELAY SCHEME

We assume that each vehicle is the source of one transmission flow and the destination of another transmission flow. Thus, there are \( n \) transmission flows in the network concurrently.

Unicast flows transmit packets via the two-hop relay scheme proposed in [15]. If the source vehicle and the destination vehicle of a transmission flow belong to the same home-point, then the source vehicle will transmit packets to the destination vehicle directly. If the two vehicles belong to different home-points, then the source and destination vehicles will relay the packets through one intermediate vehicle that has more contact opportunity with the destination vehicle.

D. DEFINITIONS OF CAPACITY

In this paper, capacity denotes the feasible throughput. The capacity of SDVANETs is defined as follows.

**Definition 1 (Feasible Throughput):** A throughput of \( \lambda(n) \) bits per second for each vehicle is feasible if there is a spatial and temporal scheme for scheduling transmissions, and every vehicle can send \( \lambda(n) \) bits per second on average to its chosen destination.

**Definition 2 (Capacity of Vehicle Network):** The average capacity of a vehicular network is on the order of \( \theta(g(n)) \)\(^1\) bits per second if there are deterministic constants \( c, c' > 0 \) and \( c < c' < +\infty \) such that

\[
\lim_{n \to \infty} \Pr(\lambda(n) = c(g(n))) \text{ is feasible} = 1
\]

\[
\lim_{n \to \infty} \inf \Pr(\lambda(n) = c(g(n))) \text{ is feasible} < 1
\]

**Definition 3 (throughput capacity):** Let \( G(T) \) denote the number of packets received by all the vehicles during time \( T \). A capacity throughput \( \lambda(n) \) is feasible if there is a scheduling scheme for which the following properties hold:

\[
\lim_{T \to \infty} \Pr \left( \frac{G(T)}{T} \geq \lambda \right) = 1.
\]

E. USEFUL KNOWN RESULTS

In this paper, we will use the following existing results.

**Lemma 1 (Chebyshev’s Inequality):** For a variable \( X \) with mean \( E[X] \) and variance \( \text{Var}(X) \), for any value \( k > 0 \),

\[
\Pr(|X - E[X]| \geq k) \leq \frac{\text{Var}(X)}{k^2}.
\]

**Lemma 2 (Groemer Inequality) [35]:** Suppose that \( X \) is a compact convex set and \( U \) is a set of points with at least one mutual distance. Then,

\[
|U \cap X| \leq \frac{\text{area}(X)}{\sqrt{3}/2} + \frac{\text{peri}(X)}{2} + 1,
\]

where \( \text{area}(X) \) and \( \text{peri}(X) \) are the area and perimeter of \( X \), respectively.

We recall the Vapnik-Chervonenkis Theorem proposed by Vapnik and Chervonenkis [36]. Let \( \zeta \) be a family of a subset of a finite set \( Q \). \( Q \) is shattered by \( \zeta \) if for every subset \( B \) of \( Q \) there is a set \( A \in \zeta \) such that \( A \cap Q = B \). The VC dimension of \( \zeta \) is denoted by \( VC - d(\zeta) \). It is defined as the maximum value \( d \) such that there is a set \( Q \) with cardinality that can be shattered by \( \zeta \). For sets of finite \( VC \) dimension, one has uniform convergence in the weak law of large numbers.

**Lemma 3 (The Vapnik-Chervonenkis Theorem):** If \( \zeta \) is a set of finite \( VC \) dimension \( VC - d(\zeta) \) and \( \{X_i|i = 1, 2, \cdots, N\} \) is a sequence of i.i.d. random variables with common probability distribution \( P \), then for every \( \epsilon, \phi > 0 \),

\[
\Pr \left( \sup_{A \in \zeta} \left| \frac{\sum_{i=1}^{N} I(X_i \in A)}{N} - P(A) \right| \leq \epsilon \right) > 1 - \phi
\]

whenever

\[
N > \max \left\{ \frac{8 \cdot VC - d(\zeta)}{\epsilon} \cdot \log \frac{16e}{\epsilon} - \log \frac{2}{\phi} \right\}.
\]

Here, \( I(X_i \in A) \) is 1 if \( X_i \in A \) and 0 otherwise.

**Lemma 4 (Borel’s Law of Large Numbers):** Let \( N(e) \) denote the number of times that \( e \) occurs in \( n \) trials, and \( p \) is the probability that event \( e \) occurs. For any positive integer \( \epsilon \), we have

\[
\lim_{n \to \infty} \Pr \left( \left| \frac{N(e)}{n} - p \right| < \epsilon \right) = 1.
\]

IV. BOUNDS ON THROUGHPUT CAPACITY OF VEHICULAR NETWORKS

A. MAXIMUM NUMBER OF CONCURRENT TRANSMISSION FLOWS

We introduce the independent set and maximum independent number to analyze the wireless transmission interference under interference relationship graph \( G_p \). The maximum independent set and maximum independent number are defined as follows.

**Definition 4 (Maximum Independent Set) [37]:** In graph theory, an independent set of an interference relationship graph is a set of vertices in which any two of them are non-adjacent. A maximum independent set is the largest independent set for a given graph.

**Definition 5 (Maximum Independent Number) [37]:** The maximum independent number of a graph is the maximum size of the maximum independent set.

In the interference relationship graph \( G_p \), that we derived above, each vertex denotes a unique unit, and the edges represent the interference relationship between vertices. If there is an edge between vertices \( i \) and \( j \), we say that vertices \( i \) and \( j \) are adjacent and have interference. Vehicles in units \( i \) and \( j \) cannot transmit during the same time slot. According to the definition of maximum independent set, each two vertices in the maximum independent set \( Y \) are non-adjacent. Thus, units denoted by the vertices in set \( Y \) cannot transmit during the same time slot. Therefore, the maximum independent

\[
\text{area}(X) + \frac{\text{peri}(X)}{2} + 1,
\]
number of a graph $G$ is the maximum number of concurrent transmission flows $M$.

As shown in Fig. 5, assume that vertices $a$, $b$, $c$, $d$, $e$, and $f$ are the vertices of the interference relationship graph $G$. The edge in the graph means that the two vertices at the end of the edge cannot transmit packets during the same slot. According to Definitions 4 and 5, vertices $a$, $b$, $c$, and $f$ compose an independent set $A$, and vertices $d$ and $e$ compose an independent set $B$. Vertices $a$, $b$, $c$, and $f$ can transmit during the same time slot. Vertices $d$ and $e$ can transmit during the same time slot. The elements of $A$ cannot transmit when any element of $B$ is transmitting. In the small interference relationship graph, we can easily find the maximum independent set $A$, and the maximum independent number is 4. Thus, in one time slot, at most 4 units can transmit packets without interference to other vertices.

We introduce a different calculation method to obtain the maximum independent number for an arbitrary network geometry and random network geometry. For an arbitrary interference relationship graph, it is easy to obtain the maximum independent number using a greedy algorithm. For a random interference relationship graph, we introduce the following Corollary from Lemma 2.

**Corollary 1:** In a square with area $S$ and perimeter $L$, suppose that $X$ is a compact convex set and $U$ is a set of points with mutual distances of at least $(1 + \Delta)r$. Then,

$$|U \cap X| \leq \frac{S}{\sqrt{3}/2(1 + \Delta)r^2} + \frac{L}{2(1 + \Delta)r} + 1.$$  

**Proof:** We lessen the Euclidean planar graph with the proportion $(1 + \Delta)r : 1$. In the original Euclidean planar graph $G$, the distance between each two elements of independent sets is greater than $(1 + \Delta)r$. In the lessened Euclidean planar graph $G'$, the distance between each two elements of the independent set is greater than 1. Simultaneously, the area and perimeter of Euclidean graph decrease proportionally. The decreased area and perimeter are denoted by $S'$ and $L'$. In a square with area $S'$ and perimeter $L'$, i.e., $S' = S/(1 + \Delta)r^2$ and $L' = L/(1 + \Delta)r$. The lessened Euclidean planar graph $G'_R$ satisfies Lemma 2, and the original Euclidean planar graph $G_R$ satisfies Corollary 1.

Clearly, the maximum independent number is the maximum number of concurrent transmission flows. We can derive the following lemma according to Corollary 1.

**Lemma 5:** In the rectangular area with side length $L$, the number of concurrent transmission flows $M$ satisfies

$$1 \leq M \leq \frac{S}{\sqrt{3}/2(1 + \Delta)r^2} + \frac{L}{2(1 + \Delta)r} + 1.$$  

**B. UPPER BOUND OF THROUGHPUT CAPACITY**

According to Lemma 5, we derive the upper bound of throughput capacity using the protocol interference model.

**Theorem 1:** For the social-proximity vehicular networks, with the two-hop relay scheme, the average throughput $\lambda(n)$ cannot be better than

$$\lambda(n) \leq \frac{\sqrt{3}/2(1 + \Delta)r^2 + L/(2(1 + \Delta)r)}{n}.$$  

**Proof:** $G_{d}(T)$ denotes the total number of packets transmitted through direct transmission from source to destination during the time interval $[0, T]$, and $G_{r}(T)$ denotes the total number of packets transmitted through relay transmission during the time interval $[0, T]$. According to Definition 3, the throughput $\lambda(n)$ satisfies

$$\frac{G_{d}(T) + G_{r}(T)}{T} \geq n\lambda(n) - \varepsilon$$  

where $\varepsilon > 0$ is an arbitrary and fixed number, and $\varepsilon \rightarrow 0$ as $T \rightarrow \infty$. $K(T)$ denotes the total transmit opportunities during $[0, T]$. The total number of transmitted packets must be less than the total number of transmit opportunities over a long period of time. Since the relay transmission needs two transmit opportunities to transmit one packet, we have

$$\frac{1}{T}K(T) \geq \frac{1}{T}G_{d}(T) + \frac{2}{T}G_{r}(T)$$  

By substituting (1) into (2), we obtain

$$\frac{1}{T}K(T) \geq \frac{1}{T}G_{d}(T) + 2\left(n\lambda(n) - \varepsilon - \frac{1}{T}G_{d}(T)\right)$$  

By sorting (3), we have

$$\lambda(n) \leq \frac{\frac{1}{T}K(T) + \frac{1}{T}G_{d}(T) + 2\varepsilon}{2n}.\tag{4}$$  

When $\varepsilon \rightarrow 0$ as $T \rightarrow \infty$,

$$\lambda(n) \leq \frac{\frac{1}{T}K(T) + \frac{1}{T}G_{d}(T)}{2n}.\tag{5}$$  

Due to the interference of wireless transmission, the total transmission must be less than concurrent transmissions during time $[0, T]$. According to the law of large numbers,
we have
\[
\lim_{t \to \infty} \frac{1}{T} K(T) \leq M. \tag{6}
\]
Similarly, we have
\[
\lim_{t \to \infty} \frac{1}{T} G_d(T) \leq M. \tag{7}
\]
The two equalities hold when there is always a transmission flow on each unit of a concurrent transmission group during each time slot. According to Lemma 5, by substituting (6) and (7) into (5), we have
\[
\lambda(n) \leq \frac{M}{n}. \tag{8}
\]
By substituting $M$ into (8), we obtain
\[
\lambda(n) \leq \frac{S}{2(1+\Delta)^2} + \frac{L}{2(1+\Delta)^2} + \frac{1}{n}.
\]
Thus, the theorem then follows. □

Remark: For an arbitrary urban region, the area $S$ and perimeter $L$ are constant. Thus, from Theorem 1, we can infer that the per-vehicle throughput $O\left(\frac{1}{n}\right)$ is feasible. Due to the physical size of vehicles and streets, the density of vehicles is always bounded by a positive number. Therefore, the number of vehicles cannot endlessly increase. The number of vehicles will approach a constant number. Before the number of vehicles reaches the constant number, the capacity of SDVANET is scaled by the asymptotic upper bound $O(\frac{1}{n})$ until the number of vehicles can no longer increase. At present, the capacity of SDVANET is also a constant number.

C. LOWER BOUND ON THROUGHPUT CAPACITY OF VEHICULAR NETWORKS

In Section II, we derived the upper bound on throughput capacity $\lambda(n)$. In this subsection, we derive the lower bound of the average throughput $\lambda(n)$ based on a two-hop relay scheme using the protocol interference model. For an arbitrary urban area, we can know the number of home-points. For a random urban area, the number of home-points is not fixed. Therefore, we propose different calculation methods for the cases of fixed and non-fixed numbers of home-points. We will prove the following lemma before we proceed to Theorem 2.

1) CALCULATION FOR THE FIXED HOME-POINT CASE

We assume that an arbitrary urban area has $N_h$ home-points and that vehicles $i.i.d.$ choose a home-point. To calculate the lower bound of capacity, we will prove the following lemma before proceeding to Theorem 2.

Lemma 6: At most $4n\left(c_1 + \frac{1}{N_h}\right)$ vehicles will co-exist in one unit concurrently w.h.p., where $c_1$ is a positive integer.

Proof: Let $N(e)$ denote the number of vehicles that belong to the same sub-area. It is easy to know that the probability that a vehicle belongs to a specified sub-area is $\frac{1}{N_h}$. According to Lemma 4, we have
\[
\lim_{n \to \infty} \left\{ \frac{N(e)}{n} - \frac{1}{N_h} \right\} < c_1 \right\} = 1,
\]
where $c_1$ is a positive integer. Thus,
\[
\lim_{n \to \infty} \left\{ N(e) < n \left( c_1 + \frac{1}{N_h} \right) \right\} = 1.
\]
According to the four color theorem, if the sub-areas do not overlap with each other, then at most one boundary is shared by four sub-areas. In this paper, the sub-areas have only little overlap with each other. Thus, at most one unit is covered by 4 sub-areas. Thus, the lemma follows.

According to Lemma 6, the transmission opportunity of at most one unit is shared by $2n\left(c_1 + \frac{1}{N_h}\right)$ transmission pairs. Since $c_1$ and $N_h$ are constant numbers, we can obtain the following theorem.

Theorem 2: For the social-proximity vehicular networks, with the fixed home-point number, the throughput capacity $\lambda(n)$ can be bounded by $\Omega(\frac{1}{n})$ w.h.p.

2) CALCULATION FOR THE NON-FIXED HOME-POINT CASE

Theorem 2 is obtained with a fixed home-point number. If we use a random map or if we cannot obtain the home-point number, we must then need the following lemma.

Lemma 7: At least $(1 - e^{-\frac{c_1}{N_p}})N_p$ units will be a home-point of at least one S-D pair w.h.p. Proof: Let $I$ be the number of units that are not chosen as a home-point of any vehicle. We define $I_i$ as an indicator variable for all units,
\[
I_i = \begin{cases} 1, & \text{if } n \in \{1, 2, \ldots, n\}, H_n \neq i \\ 0, & \text{otherwise} \end{cases}
\]
Each vehicle uniformly chooses a home-point among all units. Thus,
\[
\Pr(I_i = 1) = \left(1 - \frac{1}{N_p}\right)^{\frac{c_1}{2}}.
\]
The expectation and variance of $I_i$ are
\[
E[I_i] = \left(1 - \frac{1}{N_p}\right)^{\frac{c_1}{2}}
\]
\[
\text{Var}(I_i) = \left(1 - \frac{1}{N_p}\right)^{\frac{c_1}{2}} - \left(1 - \frac{1}{N_p}\right)^n.
\]
Next, we determine the variance of $I$. For any $i \neq j, j \in \{1, 2, \ldots, N_p\}$,
\[
\text{Cov}(I_i, I_j) = E[I_i I_j] - E[I_i]E[I_j],
\]
where $\text{Cov}(I_i, I_j)$ is the covariance of variables $I_i$ and $I_j$. Thus, $E[I_i I_j]$ is easily obtained.
\[
E[I_i I_j] = \left(1 - \frac{1}{N_p}\right)^{\frac{c_1}{2}}.
\]
Due to \( \text{Cov}(I_i, I_j) = \text{Var}(I_i) \), we have

\[
\text{Var}(I) = \text{Var} \left( \sum_{i=1}^{N_p} I_i \right) = \sum_{i=1}^{N_p} \sum_{j=1}^{N_p} \text{Cov}(I_i, I_i)
\]

\[
= \sum_{j=1}^{N_p} \text{Cov}(I_i, I_i) + 2 \sum_{i=1}^{N_p} \sum_{j=i}^{N_p} \text{Cov}(I_i, I_i)
\]

\[
= N_p \left[ \left(1 - \frac{1}{N_p} \right)^2 - \left(1 - \frac{1}{N_p} \right)^n \right]
\]

\[+ N_p(n - 1) \left( \left(1 - \frac{1}{N_p} \right)^2 - \left(1 - \frac{1}{N_p} \right)^n \right). \]

Since

\[
\left(1 - \frac{1}{N_p}\right)^2 - \left(1 - \frac{1}{N_p} \right)^n \leq 0,
\]

we have

\[
\text{Var}(I) \leq N_p \left[ \left(1 - \frac{1}{N_p} \right)^2 - \left(1 - \frac{1}{N_p} \right)^n \right].
\]

According to lemma 1, by choosing \( k = \varepsilon C \), we have

\[
\Pr(I - E[I] \geq \varepsilon C) \leq \frac{N_p \left[ \left(1 - \frac{1}{N_p} \right)^2 - \left(1 - \frac{1}{N_p} \right)^n \right]}{\varepsilon^2 C^2}.
\]

Note that \( E[I] = N_p \left(1 - \frac{1}{N_p} \right)^2 \). Thus,

\[
\Pr \left( \frac{I}{N_p} \geq \mu + \varepsilon \right) \leq \frac{\mu - \mu^2}{\varepsilon^2 C^2},
\]

where \( \mu = \left(1 - \frac{1}{N_p} \right)^2 \). If \( \rho N_p \) is used rather than \( n \), as \( N \to \infty, \mu \to e^{-\frac{\rho}{2}} \).

Therefore, \( \lim_{N \to \infty} \Pr \left( \frac{I}{N_p} \geq \mu + \varepsilon \right) \) = 0. Thus, \( \lim_{N \to \infty} \Pr \left( \frac{I}{N_p} \leq e^{-\frac{\rho}{2}} \right) = 1 \). Consequently, at least \( (1 - e^{-\frac{\rho}{2}}) N_p \) units will be a social spot of at least one S-D pair w.h.p.

According to Lemma 7, we know that one sub-area has at most \( \frac{n}{2(1 - e^{-\frac{\rho}{2}}) N_p} \) transmission pairs. Thus, during each time slot, one vehicle transmits at most \( \frac{n}{2(1 - e^{-\frac{\rho}{2}}) N_p} \) packets. Thus, we can obtain Theorem 3.

**Theorem 3:** For the social-proximity vehicular networks, with the non-fixed home-point number, the throughput capacity \( \lambda(n) \) can be bounded by \( \frac{2(1 - e^{-\frac{\rho}{2}}) N_p}{n} \) w.h.p. The result of Theorem 3 is complex in order sense; however, we can obtain constant results for the high-density urban area according to Theorem 3.

**D. AVERAGE THROUGHPUT CAPACITY OF SDVANETS**

The above content calculates the lower and upper bounds of the capacity of SDVANETs. The average throughput capacity is also important and meaningful. This sub-section will calculate the average throughput capacity of SDVANETs. We first provide the following Lemma.

**Lemma 8:** The probability of each unit having more than one vehicle during a time slot is at least \( \left(1 - e^{-\frac{\rho}{2}}\right) N_p \) with a non-fixed home-point number and \( \left(\frac{S}{N h}\right)^{-\delta/2} \) with a fixed home-point number. \( \textbf{Proof} \) : Home-points distribute uniformly in the network. According to Lemma 7, there are at least \( (1 - e^{-\frac{\rho}{2}}) N_p \) home-points in the network. Thus, every region with an area of \( S_u = \frac{S}{(1 - e^{-\frac{\rho}{2}}) N_p} \) has at least one home-point. \( P_s \) denotes the probability of each unit having more than one vehicle during a time slot, i.e., \( P_s = P_1 + P_o \), where \( P_1 \) denotes the probability of the vehicle that has home-point \( i \) at \( S_u \) during a time slot and \( P_o \) denotes the probability of vehicles that do not have home-point \( i \) at \( S_u \) during a time slot. It is easy to show that \( P_1 \geq \left(\frac{S}{N h}\right)^{-\delta/2} \) and \( P_o \ll P_1 \). Hence,

\[
P_s \geq \left(\frac{S}{1 - e^{-\rho/2}} N_p\right)^{-\delta/2}.
\]

Similarly, it is easy to obtain

\[
P_s \geq \left(\frac{S}{N h}\right)^{-\delta/2}
\]

with the fixed home-point number. This completes the proof.

We provide two definitions of probability before introducing the next lemma:

\[
p(n) = \Pr[\text{at least two vehicles on unit } i \text{ during a time slot}]
\]

\[
q(n) = \Pr[\text{finding an S-D pair on unit } i \text{ during a time slot}]
\]

Note that \( p(n) \) and \( q(n) \) are random variables because of the randomness of the location of home-points. However, we can obtain a lower bound according to Lemma 8.

**Lemma 9:** The lower bound of \( p(n) \) and \( q(n) \) is a constant \( 1 - \left(\frac{1-e^{-\rho/2} N_p}{\rho S}\right)^{\frac{\delta}{2}} \) with a non-fixed home-point number and \( 1 - \left(\frac{S}{N h}\right)^{-\delta/2} \) with a fixed home-point number.

**Proof:** We use the V-C theorem to prove this lemma. \( F \) denotes a unit, and \( P(F) \) denotes the probability that a vehicle exists at unit \( F \) during a time slot. Let \( I(Y_j \in F) \) be 1 if \( F \) contains vehicle \( j \) during a time slot and 0 otherwise. Due to the mobility of vehicles, units do not have a common probability distribution. However, units have a common lower bound of probability distribution, as we derived in Lemma 8. Let \( \Gamma \) be the class of all units. Hence, for all units \( F \),

\[
\Pr \left( \sup_{F \in \Gamma} \left| \sum_{i=1}^{n} I(X_i \in F) \right| - P(F) \right| \leq \varepsilon(n) \right) > 1 - \phi(n)
\]
whenever
\[
  n > \max \left\{ \frac{8 \cdot VC \cdot d(\Gamma)}{e(n)} \cdot \log \left( \frac{16e}{e(n)} \right), \frac{4}{e(n)} \cdot \log \left( \frac{2}{\phi(n)} \right) \right\}
\]

This condition is satisfied when
\[
  e(n) = \phi(n) = \Lambda \cdot \log(n)/n,
\]
where \( \Lambda := \max\{8VC - d(\Gamma), 16e\} \). It is easy to show that the VC dimension of \( \Gamma \) is at most 4 [36] (at least 3). Thus, we have
\[
  \Pr \left( \sup_{F \in \Gamma} \left\{ \text{number of vehicles in } F \right\} / n - P(F) \leq 16e \cdot \log(n)/n \right) > 1 - 16e \cdot \log(n)/n.
\]

For the case with a non-fixed home-point number, we simplify the above inequality, and by substituting it into the result obtained from Lemma 8, we can obtain
\[
  \Pr \left( \sup_{F \in \Gamma} \left\{ \text{number of vehicles in } F \right\} \geq n \cdot \left( \frac{S}{(1 - e^{-\rho/2})N_p} \right)^{\delta/2} - 16e \cdot \log(n)/n \right) > 1 - 16e \cdot \log(n)/n.
\]

To ensure that each unit has at least two vehicles during a time slot, the following condition has to be satisfied:
\[
  n \cdot \left( S/(1 - e^{-\rho/2})N_p \right)^{-\delta/2} - 16e \cdot \log(n) \geq 2.
\]

Since \( N_p = n/\rho \), we have
\[
  \left( \frac{1 - e^{-\rho/2}}{\rho S} \right)^{\delta/2} \geq \left( \frac{16e + 2}{n} \right) \cdot n^{-\delta/2}.
\]

Because \( n > 1 \), we obtain
\[
  \frac{16e \cdot \log(n)}{n} \leq \left( \frac{1 - e^{-\rho/2}}{\rho S} \right)^{\delta/2}.
\]

Consequently,
\[
  \rho(n) = \Pr (\forall \text{ unit } F, \text{ number of vehicles in } F \geq 2) > 1 - \left( \frac{(1 - e^{-\rho/2})\pi}{\rho S} \right)^{\delta/2}.
\]

When we prove Lemma 8, we only consider the existing probability of vehicles that have the same home-point and neglect the overlap of home-points. Thus, if two vehicles exist at a unit with the probability obtained in Lemma 8, then the two vehicles compose an S-D pair. Therefore,
\[
  q(n) = \Pr (\forall \text{ unit } F, \text{ number of } S - D \text{ pair in } F \geq 2) > 1 - \left( \frac{(1 - e^{-\rho/2})\pi}{\rho S} \right)^{\delta/2}.
\]

For the case with a fixed home-point number, we have
\[
  \Pr \left( \sup_{F \in \Gamma} \left\{ \text{number of vehicles in } F \right\} \geq n \cdot \left( \frac{S}{N_h} \right)^{-\delta/2} - 16e \cdot \log(n) \right) > 1 - 16e \cdot \log(n)/n.
\]

To ensure that each unit has at least two vehicles during a time slot, the following condition has to be satisfied:
\[
  n \cdot \left( S/(N_h\pi) \right)^{-\delta/2} - 16e \cdot \log(n) \geq 2.
\]

Thus, we have
\[
  \frac{16e \cdot \log(n)}{n} \leq \left( \frac{S}{N_h\pi} \right)^{-\delta/2} - \frac{2}{n}.
\]

Consequently,
\[
  \Pr (\forall \text{ unit } F, \text{ number of vehicles in } F \geq 2) > 1 - \left( \frac{S}{N_h\pi} \right)^{-\delta/2} + \frac{2}{n}.
\]

Theorem 4: For the social-proximity vehicular networks, the average throughput \( \lambda(n) \) is at least
\[
  \frac{1}{n} \cdot \left[ 1 - \left( \frac{(1 - e^{-\rho/2})\pi}{\rho S} \right)^{\delta/2} \right]
\]
for the non-fixed home-point number case and
\[
  \frac{1}{n} \cdot \left[ 1 - \left( \frac{S}{N_h\pi} \right)^{-\delta/2} + \frac{2}{n} \right]
\]
for the fixed home-point number case. \( \square \)

\( \text{Proof:} \) Based on the two-hop relay scheme, we use a decoupling queue structure, as shown in Fig. 6, to model unicast flows, and we consider that the packet arrival rate follows a Bernoulli process. Hence, we can represent the source vehicle \( k \) as a Bernoulli queue with service rate \( \chi_k \).

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{figure6}
\caption{Decoupled queue structure.}
\end{figure}

Let \( \tau_1^k \) and \( \tau_2^k \) denote the long-term average rate of direct transmission to destination. \( k \) is scheduled to the source. A source-to-relay transmission is scheduled to the destination. The transmission rate is denoted by
\[
  \chi_k(n) = \tau_1^k(n) + \tau_2^k(n).
\]

Thus,
\[
  \lambda(n) = \sum_{k=1}^{n} \chi_k(n).
\]

The total number of transmission opportunities during each time slot is
\[
  \sum_{k=1}^{n} \left( \tau_1^k(n) + 2\tau_2^k(n) \right).
\]
The transmission opportunity for a unit only arises when it contains at least two vehicles during the active time slot. Thus, we have

\[ M \cdot p(n) = \sum_{k=1}^{n} \left( \tau_1(n) + 2 \tau_2(n) \right). \]

Therefore, we obtain

\[ \sum_{k=1}^{n} \tau_2(n) = M \cdot \frac{p(n) - q(n)}{2}. \]

Hence,

\[ \lambda(n) = \frac{M(p(n) + q(n))}{2n}. \]

According to Lemma 4 and Lemma 9, we obtain

\[ \lambda(n) \geq \frac{1}{n} \left[ 1 - \frac{\left( 1 - e^{-\rho/2} \pi \right)}{\rho S} \right]^{\delta/2} \]

for the non-fixed home-point case and

\[ \lambda(n) \geq \frac{1}{n} \left[ 1 - \left( \frac{S}{N h \pi} \right)^{-\delta/2} \right] + \frac{2}{n} \]

for the fixed home-point case. The theorem then holds.

**Remark:** For the sparse scenario, the density of vehicles is not fixed, and the scaling law is complex. However, for the high-density area with a fixed density, we can derive the constant average throughput capacity from Theorem 4.

V. CONCLUSION

This paper analyzes the asymptotic capacity for social-proximity urban vehicular networks. We proposed a new framework that is abstracted from the real world. The proposed framework is established with a Euclidean planar graph and an interference relationship graph. The Euclidean planar graph shows the distribution of vehicles, and the interference relationship graph shows the interference relationship between each pair of vehicles. The independent set in graph theory is used to analyze the interference relationship in the interference relationship graph. With the two-hop relay scheme, an almost constant average throughput of \( \Theta(1/n) \) can be achieved \( w.h.p. \). Then this paper calculates the average throughput capacity of SDVANETs. All the calculation is under practical geometrical structure. Our results indicate that the SDVANETs are scalable to be deployed in urban environments.

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