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Modeling the Impact of Mobility on the Connectivity of Vehicular Networks in Large-Scale Urban Environments

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***Abstract*—The connectivity of moving vehicles is one of the key metrics in vehicular ad hoc networks (VANETs) that critically influences the performance of data transmission. Due to lack of in-depth analysis of real-world vehicular mobility traces, we do not understand the connectivity in realistic large-scale urban scenarios. Specifically, the mechanism of how the mobility of networked vehicles impacts the network connectivity remains unknown. In this paper, we aim to unveil the underlying relationship between the mobility and connectivity of VANETs. To achieve this goal, we employ some key topology metrics, including component speed and component size, to characterize mobility and connectivity. In our investigation of a large-scale real-world urban mobility trace data set, we discover, to our surprise, that there exists a dichotomy in the relationship between component speed and size. This dichotomy indicates that mobility destroys the connectivity with a power-law decline when the component speed is larger than a threshold; otherwise, it has no apparent impact on connectivity. Based on this observation, we propose a mathematical model to characterize this relationship, which agrees well with empirical results. Our findings thus offer a comprehensive understanding of the relationship between mobility and connectivity in urban vehicular scenarios, and based on this, helpful guidelines can be provided in the design and analysis of VANETs.**

***Index Terms*—Connectivity of network, mobility modeling, network topology, vehicular ad hoc networks (VANETs).**

I. Introduction

Urban vehicular ad hoc networks (VANETs) are recognized as a significant component of the future intelligent transportation systems [1]. Valuable information can be exchanged through the VANETs to ensure driving safety and traffic efficiency, as well as to promote new mobile services, such as content-sharing applications (e.g., advertisements and entertainments), to the public [2]. Emerging vehicular applications range from e-mail and voice messages to emergency operations, such as responses to natural disasters and terrorist attacks, etc. Equipped with wireless communication devices, vehicles can transfer data with each other or with fixed roadside infrastructure. Because vehicles typically depend on multihop communication paths to transfer data in a VANET, the connectivity of the network is of great importance in determining the network's achievable capacity. The

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mobility is one of the most important factors that influence the network connectivity. More specifically, as is pointed out in [3], the dynamic network topologies caused by the mobility of vehicles impose challenging radio propagation environments. By exploring the relationship between connectivity and mobility of networks, we can better understand the characteristics of spontaneous vehicular networks. This, in turn, will enable us to design better VANETs to achieve reliable and low-latency communications [3].

Consequently, there have been continuous investigations recently to study vehicular mobility characteristics from various perspectives, and different mobility models have been proposed. For example, on one hand, the studies [4] and [5] consider the problem in microscopic dimension by describing the acceleration or deceleration behavior of each individual vehicle. On the other hand, the work [6] focuses on macroscopic description modeling by considering the vehicles as a traffic flow instead of distinct entities. Based on these works, some conclusions have been drawn on the effects of diverse microscopic and/or macroscopic parameters. Additionally, in [7] and [8], the problem under different road assumptions, ranging from highway to urban environments is analyzed. Furthermore, a new concept of network topology has been introduced to study the mobility characteristics in VANETs.

With the concept of network topology, researchers can analyze the mobility characteristics of a vehicular network from a network perspective. For example, the empirical studies [9] and [10] have investigated the instantaneous topology of a large-scale urban vehicular network. More specifically, Naboulsi and Fiore [9] studied the availability, connectivity, and reliability of urban vehicular networks. Due to the lack of real-world vehicular mobility data sets, however, the study [9] is conducted based on a synthetic vehicular data set, which is far from a real-world situation and cannot reflect the real vehicular behaviors in urban scenarios, leading to potentially inaccurate analysis. Luo *et al.* [10] presented the characteristics of Shanghai trace, which involves taxis, in their study, and they use this real-world vehicular data set in simulation to discuss the connectivity and network performance, including link duration, average hops, and connection rates. They find that more than 80% of taxis can be integrated into a single ad hoc network in certain time periods if the communication range is over 500 m, which can provide a good network performance. The metrics selected in their study benefit the network analysis, but this study only describes the key mobility characteristics rather than discovering which underlying factors can affect them. Currently, we still lack quantitative and fundamental understanding of the connectivity and how other key factors can influence it in a large-scale urban scenario.

This is despite the fact that there exist many studies investigating the potential impacting factors of the connectivity, including the factors such as topology, traffic signals, and vehicle traffic [4], [7], [11]. For example, Marfia *et al.* [11] focused on the stop-and-go behavior of traffic to study how it can cause network congestion and affect the connectivity. Artimy *et al.* [7] investigated connectivity in VANETs and examined how the relative velocity and the number of lanes impact on the connectivity. However, among various potential factors that influence the connectivity, the mobility is of great importance. Some studies [4], [12]–[16] do aim to explore the relationship between connectivity and mobility. However, these works neither study this relationship in vehicular networks [12]–[14] nor analyze the problem using real-world vehicular data traces [4], [15], [16]. Thus, there exist no studies that reveal the fundamental relationship between mobility and connectivity in large-scale urban vehicular networks.

In this paper, we employ the real-world mobility traces from about 4000 taxis recorded for over one month in Shanghai, China, for analysis. Compared with the studies based on synthetic traces or analytical tools, this brings great advantages because the large-scale real-world vehicular motions recorded in these traces can reflect the real situations in large-scale urban environments to a greater degree. Moreover, to the best of our knowledge, there is no existing work studying how the mobility of a vehicular network impacts its connectivity, as measured by the topology metric known as component size, based on real experiments. Thus, we are the first to unveil the fundamental relationship between mobility and topology of large-scale urban vehicular networks.

We emphasize that the connectivity can be studied based on some fundamental topology characteristics, in particular, a key metric referred to as component size. A larger component size indicates that more vehicles are successfully connected together with multihop communication, and the connectivity is therefore better. Moreover, the connectivity can be judged by the number of vehicles linked to a certain vehicle. Thus, for the sake of clarity, we consider the connectivity of a large-scale urban vehicular network in the view of network topology characteristics, and we endeavor to reveal the relationship between mobility and topology. In this way, we discover to our surprise that when the component speed is larger than a threshold, which is between 18 and 20 m/s in our study, there is a power-law relationship between the component speed and the corresponding component size, whereas when the component speed is smaller than this threshold, the relationship between the component size and speed changes into a uniform distribution. This dichotomy in the relationship of component size and speed indicates that mobility destroys the connectivity when speed is larger than a threshold; otherwise, it has no apparent influence on the connectivity. Based on the above observation, we propose a mathematical model to characterize this relationship, which agrees well with empirical results.

The rest of this work is structured as follows. In Section II, we describe the data set and preprocessing used in our study, as well as present models and define key mobility characteristics. In Section III, we first analyze the distributions of typical mobility characteristics, such as vehicular speed, component speed, and component size. Then by using subplots and scatterplots, we study the relationship between mobility and connectivity. In Section IV, we further propose a mathematical model to characterize the relationship between mobility and connectivity. Finally, we conclude our work in Section V.

II. Data Set and Key Metric Definitions

We first provide a brief description of the mobility data set used in our study and the preprocessing carried out on the data set. Then, to explore the relationship between the connectivity and mobility of VANETs, the related network model and key performance metrics are described.

A. Data Set and Preprocessing

To investigate realistic vehicular mobility and connectivity in urban scenarios, we conduct a study on Shanghai trace [17] collected by the SG project [18], in which mobility trace data from over 4000 taxis were collected during the whole month of February 2007 in Shanghai. In this trace, reports were continuously sent back to the data center by General Packet Radio Service. Specifically, the frequency of reports was either every 1 min when a taxi had passengers on board or every 15 s when it was vacant. The information reported included the taxi's ID, the longitude and latitude coordinates of the taxi's location, the speed, and other factors such as heading and the status of the taxi.

In our study, we preprocess the data set in the following way. To analyze the vehicular mobility and connectivity, we need to know the exact location of every taxi in a large number of time points. Therefore, it is of great importance to sample appropriate time points with a fixed frequency to obtain the real-time topology. Since Global Positioning System reports were collocated in discrete time at the time interval of 15 s or 1 min, we sample the time points every 10 min. A new real-time topology is obtained every 10 min, and in this way, we collect 144 topologies in 24 h. After empirical data processing, we found that it is an acceptable sampling frequency because most of the sampled topologies have no significant change in just 10 min.

B. Model and Metrics

Our analysis targets at the relationship between the topology and mobility of a vehicular network. To achieve this objective, we borrow tools from the complex network theory, which are employed to depict the characteristics of large-scale networks. Therefore, we offer the details of how we model an instantaneous vehicular network topology and the key metrics used in our study.

As described above, we have a large number of instantaneous topologies by sampling the data with a fixed frequency. We model the topology at each sample time point as a graph $G(N, E)$ and consider the successful communication link between two vehicles as an edge between these two nodes in the graph. In this way, we define the related notations as follows. The graph G contains a set of the nodes that are labeled by $N = \{n_i\}$ and a corresponding edge set represented by $E = \{e_{i,j}|n_i, n_j\}$, in which $e_{i,j}$ depicts the link between vehicle i and vehicle j.

We consider the establishment of communication links by a simple unit disk model. That is, we denote the unit disk communication range as R to judge whether a successful link is established. More specifically, when the distance between two vehicles is smaller than R, we assume that there is a communication link established between them. We recognize that this model only offers an upper bound capacity of the network, as whether successful data transmission can be achieved on a link depends on many other random factors. Compared with other signal propagation models, such as ray tracing, this unit disk model greatly reduces the associated computational complexity, and it scales well in our analysis of large-scale topology and mobility. Basically, this model captures the behaviors of a network in a simple yet an efficient way. We note that only bidirectional links are considered in our experiment due to the adoption of this unit disk model. We now offer the following definitions that describe some key characteristics of VANETs.

Definition 1 (Component): Consider a topology obtained in a certain time point t. We have a graph $G(N, E)$ consisting of its node set N and edge set E at t. If we associate the nodes $\{n_i\}$ with each other as long as there exist paths represented by the edges between them, then a subgraph at t, which is denoted by $C(t)$, can be obtained, which defines a *component*. Let us also denote $p_{i,j}(t)$ as the shortest multihop communication path between two vehicles i and j at t, which is the ordered sequence of nodes in the shortest path, i.e., $p_{i,j}(t) = \{n_i, \ldots, n_j\}$. Then, the component $C(t)$ contains a subset of nodes, which is denoted by $C(t) = \{n_i \bigcup n_j | n_i, n_j \in N \bigcap p_{i,j}(t) \neq \emptyset\}$, and a subset of the edges, which is denoted by $E_C(t) = \{e_{i,j}|n_i, n_j \in C(t)\}$.

We employ the component $C(t)$ to represent the network within which each vehicle can reach any other vehicle at time t by multihop connections. The size of the component is the number of nodes belonging to it, namely

$$S(t) = \|C(t)\|.$$

In the sequel, we will drop the time index t to simplify notations, and we simply denote the component by C and the size of the component by S, which are two key metrics in our study.

Definition 2 (Vehicular Speed): We use the vehicular speed v to describe the mobility of an individual vehicle. For $n_i \in N$, the vehicular speed of n_i is denoted by v_{n_i}.

Definition 3 (Component Speed): The component speed V is defined as the average value of all the vehicle speeds in the same component, representing the mobility of the component. With S representing the size of component C, the component speed V is given by

$$V = \frac{1}{S} \sum_{n_i \in C} v_{n_i}.$$

In the network topology terminology, the vehicular speed refers to the movement of a node per unit time, showing the individual motion from a node level. By contrast, the component speed reflects the mobility at the component level, which is a more macroscopic metric than vehicular speed. Given all the vehicles in the same component, the component speed provides us the mobility of the network, instead of an individual vehicle. We emphasize this because the component speed gives us more mobility information from a network perspective.

III. Analysis of the Vehicular Mobility and Connectivity

To better understand the mobility and connectivity of vehicular networks, we first investigate the distributions of the related metrics, such as vehicular speed, component speed, and size. Then we analyze the relationship between component speed and component size.

A. Distributions of Speed and Component Size

We start our analysis by considering the mobility and connectivity of the vehicular network, respectively. For the sake of clarity, in our study, we initially set the communication radius R to a particular value of 600 m, which is a reasonable value reflecting realistic situations and is consistent with current device-to-device communication technologies. As is shown in [19], it is practical and realistic to set R to 600 m because the maximum potential connection can span up to a distance of 1280 m, which lasts 58 s at a speed of 80 km/h. Furthermore, the previous work [9] also suggests that the giant cluster comprising more than 50% of the vehicles is presented all the time, which demonstrates the stable connectivity within large clusters over time.

We study the mobility characteristics of vehicular networks through the two metrics: the vehicular speed, showing the individual motion from a node level, and the component speed, reflecting the motion from a component level. We draw the cumulative distribution function (CDF) and the complementary CDF (CCDF) of both the vehicular speed and component speed in Fig. 1 to have a closer look. From the CDF results shown in Fig. 1, we observe that when the vehicular speed and component speed are between 10 and 100 m/s, the vehicular speed and component speed both exhibit exponential distributions, whereas the CCDF results in Fig. 1 indicate that the probability distributions of the vehicular speed and component speed both exhibit a similar exponential decay over all the speed range. Moreover, it can be seen that over 80% of the vehicles have vehicular speeds smaller than 40 m/s and around 40% of the vehicle speeds are smaller than 10 m/s. Similarly, over 80% of the component speeds are smaller than 45 m/s, and around 40% of them are smaller than 10 m/s. Therefore, both the vehicular speed and component speed exhibit exponential distributions with very similar parameter values.

To study the distribution of the component size, which depicts the connectivity of the network, we plot both the CDF and CCDF of the component size when aggregating over all the samples of S in Fig. 2.

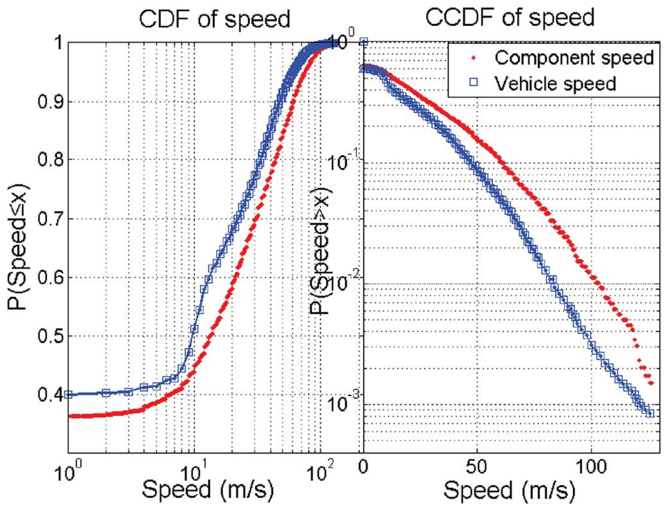

Fig. 1. (Left) CDF and (right) CCDF of the vehicle speed and component speed over six days, covering 144 h.

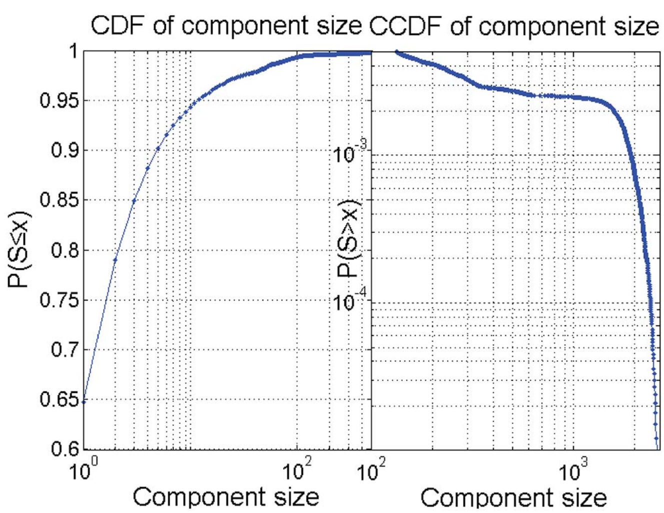

Fig. 2. (Left) CDF and (right) CCDF of the component size when aggregating all the samples of S over six days.

With the help of the component size's distribution, for example, we can examine whether the component size is heterogeneous or not. The CDF shown in Fig. 2 shows that around 80% of the components are composed of 20 vehicles or less, and it also indicates that 65% of the vehicles are isolated vehicles, losing contact with other vehicles. Moreover, a heavy tail of the distribution appears as linear on a log–log scale in the CCDF when the component size is larger than 1000. These observations are important, as the component size distribution reflects how a heterogeneous network distributes and therefore, to some extent, represents its characteristics.

The distributions in Figs. 1 and 2 provide us a fundamental understanding of the key metrics of component speed and size, which is of great importance in studying the network mobility and connectivity, as well as in understanding their relationship.

B. Relationship Between Mobility and Connectivity

To reveal the relationship between mobility and connectivity, we conduct an empirical analysis of the component speed and component size. We start with an overview about this relationship and then proceed to provide more details.

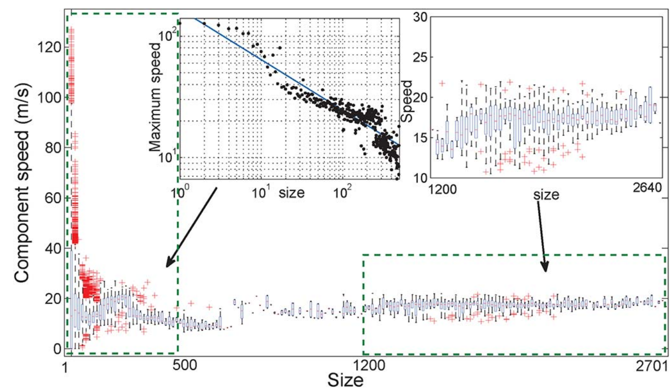

Fig. 3. Boxplot depicting the overview of the relationship between component speed and component size for communication range $R = 600$ m. With a log–log scale, the scatterplot (top left) illustrates the maximum component speed versus the component size, whereas the subplot (top right) presents more details with an enlarged scale.

We draw a boxplot in Fig. 3 to explore the relationship of the component speed versus the component size, from which we may obtain a general relationship between mobility and connectivity. In this boxplot, every blue strip represents the component speed distribution with an x-axis width of 15, i.e., a width 15 in component size, whereas the length of a blue strip in the y axis indicates the interquartile range of the component speed, reflecting the variability of the component speed. Additionally, each black dashed line represents the corresponding maximum and minimum values, whereas the red plus symbols indicate extreme outliers. From the boxplot in Fig. 3, we observe a dichotomy in the relationship of the component speed versus the component size, partitioned by the component speed of around 20 m/s. Basically, the distribution exhibits very different properties when the component speeds are smaller and larger than 20 m/s, respectively.

To better understand this dichotomy relationship of the component speed versus the component size, we study the two parts of its distribution in detail. We first draw the scatterplots of the maximum component speed versus the component size in the top left subplot in Fig. 3 with the component size range up to 500. Using a log–log scale, we can appreciate a power-law decaying relationship from the fact that most plots are on or near the straight blue line with a fixed slope. Thus, for the component speed larger than 20 m/s, the component speed clearly exhibits a power-law decaying relationship with the corresponding component size. To analyze the relationship when component speeds are smaller than 20 m/s, we draw another boxplot in the top right subplot in Fig. 3 for the component sizes between 1200 and 2640, where an x-axis width of 30 is used. Clearly, we have a uniform distribution when the component speeds are smaller than 20 m/s.

For the sake of verifying whether the dichotomy of this relationship is a generic one, covering different time periods of the day, we draw two boxplots in Fig. 4 for the component speed versus size, which involves two different time periods of the day. Specifically, we skip the morning and afternoon rush hours to focus on the normal A.M. time (00:00–07:00 and 09:00–12:00) and the normal P.M. time (12:00–17:00 and 19:00–24:00). An x-axis width of 200, i.e., a width of 200 in component size, is used in this figure. From Fig. 4, it can be seen that similar patterns exist in the two different time periods. More specifically, in both time periods, the components containing less than 200 vehicles, which make up the main part of the network, have similar component speed contributions. The only noticeable difference is that compared with the A.M. time period, in the P.M. time period, there is hardly any vehicle component with size between 600 and 1400. Obviously, vehicles travel faster in the nighttime than in the daytime.

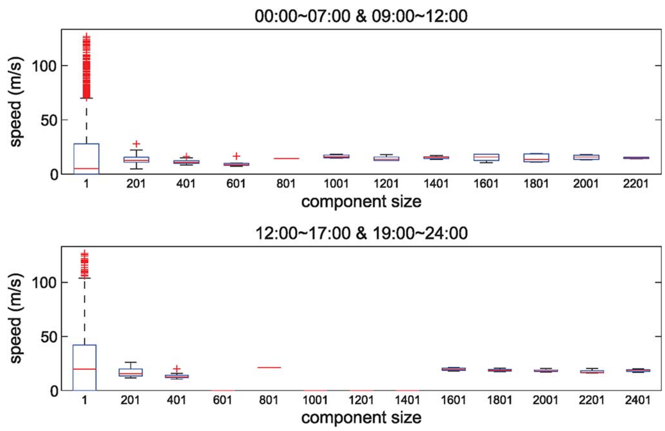

Fig. 4. Component speed versus component size in A.M. time (00:00–07:00 and 09:00–12:00) and in P.M. time (12:00–17:00 and 19:00–24:00).

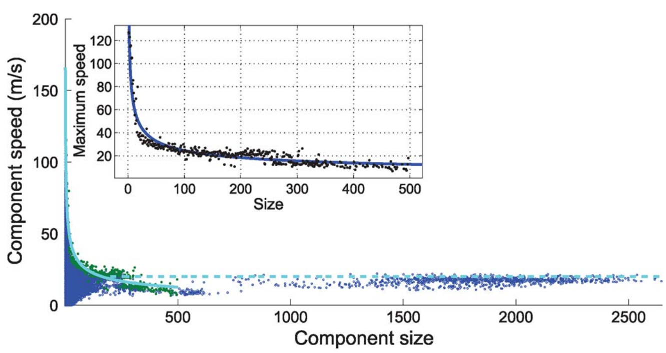

Fig. 5. Scatterplots of the component speed versus component size represented by blue spots. The green spots correspond to the maximum component speeds for the component size up to 500, the light blue curve is a power-law fitting, and the light blue dashed line corresponds to the component speed of 20. Note that the top right subplot shows the power-law fitting in the blue curve, where the black spots correspond to the green spots in the main plot.

IV. Dichotomy Model and Validation

Based on the above empirical results and observations, we propose a dichotomy model characterizing the relationship between the mobility and connectivity of vehicular networks. The relationship exhibits a dichotomy partitioned by a certain component speed threshold or constant A, which we refer to as the *characteristic component speed*. In our case study of Shanghai trace, the characteristic component speed is between 18 and 20 m/s.

To describe the dichotomy of this relationship, we use mathematical tools and conduct regression analysis to obtain the related function fittings for the component size S as follows:

$$S = \begin{cases} \alpha \cdot x^{\beta}, & \text{component speed} \geq A \\ \text{any value in } S_{\min} \text{ to } S_{\max}, & \text{component speed} < A. \end{cases}$$

In the above model, both $S_{\min}$ and $S_{\max}$ are network-specific integers, whereas the values of the parameters α, β and A are obtained by fitting the model to the data.

In Fig. 5, we plot the component sizes and corresponding speeds directly from the trace data as blue spots. Additionally, the component sizes up to 500, and their corresponding maximum component speeds are shown in Fig. 5 as green spots. We next fit the above dichotomy model to the data and depict the resulting $S = \alpha \cdot x^{\beta}$ with $\alpha = 166.1$ and $\beta = -0.4148$ as the light blue curves, as well as plot a light blue dashed horizontal line corresponding to the component speed of 20. It can be seen from Fig. 5 that our dichotomy model explains the empirical data extremely well. On one hand, when the component speed is larger than $A = 20$ m/s, the power-law fitting model reflects the true relationship between the component size and the corresponding maximum component speed. As mentioned previously, the component speed describes the mobility, whereas the component size depicts the connectivity of network. Thus, this power-law relationship indicates that for the component speed larger than A, the mobility destroys the connectivity with a power-law decay. The faster a vehicle moves, the fewer vehicles it can successfully connect with due to the smaller component size. On the other hand, when the component speed is smaller than A, this relationship changes into a uniform distribution, in which the component speed may correspond to any component size, ranging from the minimum size $S_{\min} = 1$ to the maximum size $S_{\max}$. In other words, the mobility when lower than a threshold has no apparent impact on the connectivity of the network. Clearly, our model is built according to this empirical dichotomy phenomenon. In addition, we observe from Fig. 5 that the components with sizes between 200 and 500 are in a "special" situation as their corresponding speeds are smaller than $A = 20$ m/s. They fit well with a power distribution but can also be explained by a uniform distribution. Thus, we may treat this part as a transitional zone. This makes sense as it just proves that there are no abrupt changes in the dichotomy of the relationship in reality.

To verify the accuracy of our dichotomy model of the power-law distribution and the uniform distribution, we measure the goodness of fit quantitatively by the R-square statistics, which is defined as the percentage of the variation between the empirical CCDF and the fitted distribution. In particular, when we employ our model $S = \alpha \cdot x^{\beta}$ with $\alpha = (159.1, 173.1)$ and $\beta = (-0.426, -0.4035)$ as 95% confidence bounds, the adjusted R-square is equal to 87.88% for the statistics of the power-law fitting to the empirical data of component speed versus size. This confirms the accuracy our dichotomy model of the relationship between mobility and connectivity.

V. Conclusion

In this paper, we have revealed an interesting and somewhat surprising dichotomy relationship between the mobility and connectivity of VANETs based on an in-depth empirical analysis of a real-world large-scale Shanghai trace data set. This dichotomy indicates that mobility destroys the connectivity with a power-law decline when component speed is larger than a threshold; otherwise, it has no apparent impact on connectivity. We have proposed a mathematical model, which fits extremely well with this dichotomy relationship, to describe how the network mobility impacts on the connectivity in large-scale urban scenarios. Our findings thus have provided helpful guidelines for design and analysis of VANETs, which demand good understanding of the relationship between mobility and connectivity in urban scenarios. For example, because we are able to estimate the speed range according to the demand of connectivity with our model, when designing an exchange protocol for vehicular applications, an optimum range of speed can be obtained to ensure successful data transmissions. In this way, a more accessible and flexible communication will be achieved. Similarly, the proposed mathematical model enables us to estimate the connectivity situations given the vehicular mobility, and this knowledge of the network connectivity is valuable in the daily operation of a VANET. In this paper, we focus on the impact of mobility on the connectivity of VANETs, as the mobility is a main factor that affects the connectivity. There are other factors that also affect the connectivity. Future work is warranted to rigorously investigate their relationships with the connectivity.

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On the Energy Efficiency and Effective Throughput Tradeoff of Fading Channels

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***Abstract*—This paper investigates the tradeoff between the energy efficiency (EE) and the effective throughput (ET) of fading channels. In particular, we consider the case of zero channel state information (CSI) at the transmitter, and thus, the receiver can only successfully decode the source messages with certain probability. Accordingly, the ET, which is defined as the rate of the successfully decoded information, is adopted to measure the spectrum efficiency of the considered channels. We characterize the EE–ET region by exploiting its structure, and each boundary point is obtained by solving a quasi-concave problem. As a special case, we also obtain the maximum ET per unit energy in closed form. Finally, we generalize our results to the case of multihop relay channels.**

***Index Terms*—Capacity per unit energy, effective throughput (ET), energy efficiency (EE), fading channel.**

I. Introduction

With the increasing demands for green communications [1]–[3], it has become an inconvertible trend that modern wireless systems are expected to achieve the same level of quality of service as the conventional systems, while consuming much less energy. Along this avenue, designers emphasize more and more on the energy efficiency (EE) [4]–[6] of the considered systems, which is defined as the transmitted bits per unit energy, beyond the spectrum efficiency (SE), which is equal to the information transmission rate. It has been shown in the literature (see [1], [2], and the references therein) that there exists an interesting EE-versus-SE tradeoff for various wireless communication systems, i.e., increasing EE will decrease SE, and vice versa. The EE–SE region plays as a fundamental limitation for various wireless communication systems and provides an important guideline for designing the physical-layer transmission schemes under different EE and SE requirements. For example, by assuming perfect channel state information (CSI) at the transmitter, Xiong *et al.* in [7] first characterized the EE–SE tradeoff for the downlink orthogonal frequency-division multiple-access networks, and some upper and lower bounds were obtained.

In this paper, we focus on a block-fading channel, with zero CSI at the transmitter, and a delay-constrained traffic is considered, for which the transmission rate in each block should be no smaller than R. Under this scenario, it is easy to see that the receiver can only successfully decode the source messages with a probability less than 1. Instead of using the conventional Shannon capacity [5]–[7] as the measure for SE, we thereby adopt the effective throughput (ET), i.e., the rate of the successfully decoded information at the receiver, as

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