Data-Driven Optimal Throughput Analysis for Route Selection in Cognitive Vehicular Networks

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***Abstract*—To meet the dramatically increasing demands for vehicular communications, cognitive vehicular networks have been proposed to broaden the vehicular communication bandwidth by using cognitive radio technology. Meanwhile, the nationwide Super Wi-Fi project that allows the TV white space frequencies to be used for free, makes the concept of cognitive vehicular networks realistic. Recently, lots of technical issues of cognitive vehicular networks have been studied from the network designers' perspective, e.g., vehicular spectrum sensing and access, applications with different vehicular QoS, etc. Different from the existing works, in this paper, we consider from the vehicular users' perspective by optimizing throughput via route selection in cognitive vehicular networks using TV white space. By employing the attainable data rate as route selection metric, we propose two schemes: instantaneous route selection and long-term route selection. To evaluate the expected data rate on the route, we analyze the cognitive vehicular network throughput under two spectrum sharing models: spectrum overlay and spectrum underlay. In the experiments, we use Google spectrum dataset to estimate the intensity of TV base stations in the United States and evaluate the cognitive vehicular network throughput performance, which shows that the spectrum overlay model is more suitable for most of states in current United States, except New Jersey, Delaware and Utah. Moreover, we conduct a case study regarding the route I-88E and I-90E selection between Cortland and Schenectady in New York State. The traffic intensities and traffic intensity transition probabilities of these two routes are estimated using the real-world traffic volume dataset of New York State. Based on the estimated traffic information, we calculate the attainable instantaneous and long-term data rates of each vehicular user, which shows that route I-88E is preferable to route I-90E in most cases.**

***Index Terms*—Cognitive radio, cognitive vehicular networks, Point Poisson Process, route selection, spectrum underlay and overlay, TV white space, vehicular communication.**

I. Introduction

With the rapid development of new wireless applications and devices, the last decade has witnessed a dramatic increase in the demand for electromagnetic radio spectrums. Traditional static spectrum allocation policy has leaded to more and more crowded available spectrum resources [1]. Under such circumstance, cognitive radio (CR) technology is becoming a promising communication paradigm, which can greatly enhance the utilization efficiency of the existing spectrum resources [2]. In CR, cognitive devices, called as Secondary Users (SUs) are allowed to dynamically access the licensed spectrum of Primary Users (PUs) [3]. CR has been applied in various new wireless technologies, e.g., in WiFi [4], tactical networks [5], cooperative communications [6], etc.

Recently, one prominent application of CR is in the vehicular communication systems, called as cognitive vehicular networks [7]. Vehicular communications were originally proposed for the guarantee of public safety and avoidance of traffic collisions, which aims to provide reliable and short-distance vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [8]. Nowadays, with the development of automobile technology, people's mobility grows exponentially, e.g., Americans ride 224 miles or more per week either as a driver or passenger and the total time spent traveling in a vehicle per week is about 18 hours and 31 minutes [9]. Meanwhile, the vehicular users' demands for in-car communication are also increasing dramatically, e.g., lots of value-added services emerge such as safety messages dissemination [10] and in-car entertainment service [11]. However, IEEE 802.11p standard only allows the vehicular communication to use the 5.9GHz band (5.850 – 5.925 GHz) with 75MHz bandwidth, which apparently may not satisfy people's exponentially increasing demands for vehicular communication in the near future [12]. This problem can be solved by deploying the vehicular networks in the TV white space using CR technology, which can broaden the vehicular communication bandwidth to a large extent. Such a cognitive vehicular network solution over TV white space is emerging since the United States Federal Communications Commission (FCC) has launched the nationwide Super Wi-Fi project that allows the TV white space frequencies to be used for free [13].

In this paper, we consider the route selection problem in cognitive vehicular networks using TV white space. Nowadays, by using the online map services, e.g., Google maps and Apple maps, people can be suggested with several routes from one location to a desired destination, where the route recommendations are usually either distance-aware or time-aware. Considering the increasing demands for vehicular communications, we propose to add another route selection metric: the network throughput on the route, which is closely related with the number and locations of TV base stations along the route, as well as the traffic intensity and traffic intensity transitions. In this paper, we will study how to incorporate these factors into the route selection problem. The contributions of this paper can be summarized as follows.

1) We consider the route selection problem in cognitive vehicular networks with the concept of network throughput metric. Two route selection schemes are proposed:

Manuscript received Jan 5, 2014; revised Apr 24, 2014. This work was partly funded by project 61371079, 61273214 and 61271267 supported by NSFC China, National Basic Research Program of China (973 Program) under grants 2013CB329105 and Postdoctoral Science Foundation funded project. This work was done during C. Jiang's visit at the University of Maryland.

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Digital Object Identifier 10.1109/JSAC.2014.141116.

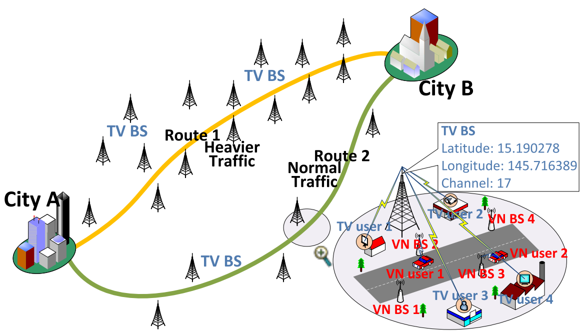

Fig. 1. System model.

instantaneous route selection and long-term route selection. For the instantaneous scheme, the vehicular users make route selection only according to the immediate traffic conditions; while for the long-term scheme, they also take into account the traffic condition transitions in the near future by calculating the long-term expected data rate on the route.

2) We analyze the cognitive vehicular network throughput under two spectrum sharing models: spectrum overlay and spectrum underlay. By modeling the locations of TV base stations as Point Poisson Process distribution, we analyze the interference of vehicular user to the TV users, and derive the vehicular users' optimal transmission power and achievable downlink throughput.
3) We use Google spectrum dataset [14] to estimate the intensity of TV base stations in the United States, and evaluate the cognitive vehicular network throughput under both spectrum overlay and underlay models. The experiment results shows that for current United States, the spectrum overlay model is more suitable, except three states: New Jersey, Delaware and Utah.
4) We study the route I-88E and I-90E selection between Cortland and Schenectady in New York State. By using the real-world traffic volume dataset, we first estimate the traffic intensities and traffic intensity transition probabilities of these two routes. Then, the instantaneous and long-term data rates obtained by each vehicular user are evaluated, which shows that route I-88E is preferable to route I-90E in most cases.

The rest of this paper is organized as follows. The related works are presented in Section II. Then, we discuss the proposed instantaneous and long-term route selection schemes in Section III. The vehicular network throughput under spectrum overlay and underlay models are analyzed in Section IV. In Section V, we conduct real-world data-driven experiment to evaluate the route selection performance. Finally, the conclusions are drawn in Section VI.

II. Related Works

In the literature, the cognitive vehicular networks have been studied in several aspects, including spectrum sensing, spectrum access, spectrum management and applications. In [15]-[19], the cooperative spectrum sensing for cognitive vehicular networks were studied, including sensing coordination method [15], belief propagation method [16], location based method [17] and database integration methods [18][19]. In addition to channel sensing, the channel access for cognitive vehicular networks were investigated in [20]-[24], including distributed channel coordination [20], cognitive MAC-layer protocol design [21], spatially-aware channel selection [22], QoS-aware channel access management [23] and game theoretic analysis [24]. Moreover, the spectrum management related issues were analyzed [25]-[27], where Felice *et al.* proposed a cooperative spectrum management scheme in [25], Ghandour *et al.* focused on the scenario of congested vehicular Ad hoc networks in [26] and Doost *et al.* designed the database assisted solution in [27]. Meanwhile, some applications based on the cognitive vehicular networks were also discussed [28]-[31], including the safety and reliability guarantee in [28][31], cognitive emergency network in [29] and enhance broadcast vehicular communication in [30]. Furthermore, some practical experiments and evaluations were also conducted in [32]-[33], including channel modeling [32] and a demonstration of cognitive vehicular network in TV white space [33].

The aforementioned prior works mainly focused on the technical design of cognitive vehicular networks from the network designers' perspective, such as cooperative spectrum sensing scheme design, primary channel access and coordination scheme design, applications design with different QoS standards, etc. Different from these existing works, in this paper, we consider from the vehicular users' perspective by optimizing throughput via route selection in cognitive vehicular networks using TV white space. In the literature, the throughput of cognitive networks in TV while space has also been investigated, e.g., mobile terminal's achievable data rate with channel query constraint [34], LTE-advance downlink throughput evaluation [35] and the capacity analysis of Wi-Fi system in TV white space [36]. In addition, power control of cognitive networks in TV white space has also been studied, e.g., database-driven transmission power allocation scheme design in [37] and uplink power control for TD-LTE in TV white space in [38]. Those existing works only considered the TV white space in terms of time and frequency domains. However, the locations and distributions of TV base stations have not been taken into account, which, however, also affect the vehicular users' throughput to a large extent. In this paper, by modeling the locations of TV base stations as Point Poisson Process distribution, we analyze the interference of vehicular user to the TV users, and derive the vehicular users' optimal transmission power and achievable downlink throughput.

III. Route Selection in Cognitive Vehicular Networks

We consider a heterogenous network with licensed digital TV base stations (BSs) and TV users regarded as PUs, as well as unlicensed vehicular network (VN) BSs and VN users regarded as SUs, as shown in the zoom-in sub-figure of Fig. 1. The cognitive VN BSs and VN users are allowed to opportunistically utilize the TV spectrums under the condition that the TV users' communication QoS is guaranteed. Suppose one VN user intends to travel from City A to City B as shown in Fig. 1, where he/she is suggested with two possible routes by the online map service providers, e.g., Google maps. Nowadays, travel distance and time are the only two metrics

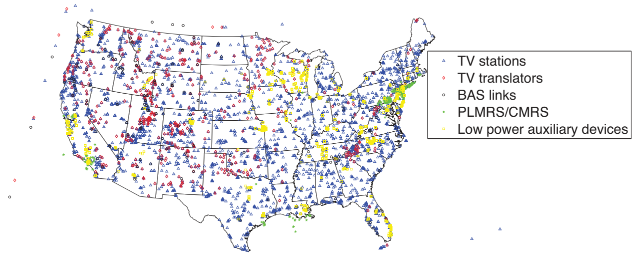

Fig. 2. Distribution of TV BSs in the United States abstracted from Google spectrum database [14].

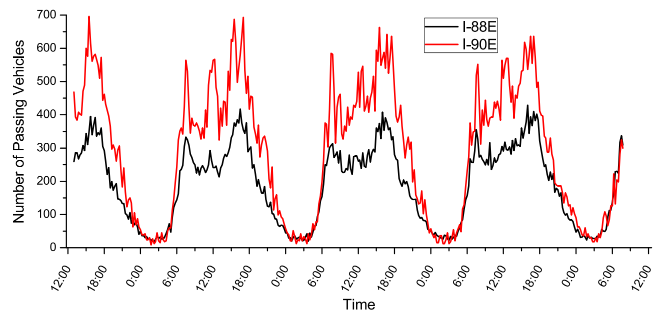

Fig. 3. Traffic volume of route I-88E and I-90E.

that considered by the map providers, i.e., the recommended routes are either with shorter distance or shorter travel time calculated based on current traffic condition. For example, in Fig. 1, Route 1 would be recommended if shorter distance is preferred, while Route 2 would be recommended if lighter traffic condition is preferred.

As we discussed in the introduction, considering the fast-growing demands for vehicular communications, we propose the attainable data rate as another principal metric that considered by a cognitive VN user when making route selections. Firstly, due to the fact that the cognitive VN BSs can only utilize the unoccupied TV channels, the more TV BSs are located along a certain route, the less spectrum opportunity can be obtained by the cognitive VN users. As illustrated in Fig. 1, the density of TV BSs along Route 1 is obviously larger than that along Route 2. In such a case, the available spectrum is less and the vehicular network throughput on Route 1 would be lower than that on Route 2. Secondly, the traffic intensity also plays an important role in route selection since the nearby cognitive VNs have to share the same vehicular network base station. In such a case, the higher traffic intensity would lead to the more vehicular users simultaneously sharing the same channel resources, which would inevitably impair each VN user's data rate. Therefore, both the TV BSs along the route and traffic conditions on the route can influence a VN user's expected data rate, which, in turn, affects the VN user's route selection result. In the following, we summarize the fundamental factors that influence the VN users' route selection.

1) *TV BSs:* In general, the VN users prefer to the route in the area with less intensity of TV BSs and more TV white spaces. In Google spectrum database, the information of all the TV stations in the United States can be accessed, as well as the auxiliary infrastructures including the TV translators, the Broadcast Auxiliary Service (BAS) links, the PLMRS/CMRS (Private Land/Commercial Mobile Radio Services) base station operations and the Low Power Auxiliary Devices [14]. The information of these TV BSs contains the occupied channel frequency, the antenna information and the location information, i.e., the latitude and longitude. As shown in Fig. 2, we abstract the location information of all kinds of TV BSs and depict it on the map of the United States except Alaska and Hawaii. From the figure, we can see that different states have different intensities of TV BSs, and TV stations in the northeast areas are denser than other areas. In this paper, we will use those real-world TV BSs data traces to estimate the intensity of TV BSs in different states and evaluate the vehicular network throughput based on the estimated intensity information.

2) *Traffic Intensity:* Similar to the traditional time metric, the traffic intensity also influences the cognitive VN user's expected data rate on the route. The vehicular network throughput is in terms of one VN user; while when it comes to multiple VN users, the characteristic of negative network externality should be considered [39], i.e., the more users access the same VN BS, the less data rate can be obtained by each individual VN user. For example, let us consider two recommended routes between Cortland and Schenectady in New York State of the United States: route I-88E and I-90E. Based on the traffic volume dataset provided by the the Department of Transportation of New York State [40], we show the number of vehicles on these two routes in Fig. 3, which shows that the traffic on route I-90E is averagely heavier than that on route I-88E. In this paper, we will use those real-world traffic data traces to evaluate the VN user's expected data rate and the route selection result.

3) *Dynamic Traffic:* As we know, the real-time traffic intensity is not static but keeps changing with time, as shown in Fig. 3 where the traffics in the rush hours would be much heavier than that in the regular hours. In addition, different routes may have different traffic intensity transitions. In such a case, when making a route selection, a cognitive VN user should not only consider the current traffic intensity, but also needs to take into account the traffic intensity changes in the near future. Therefore, the dynamic traffic intensity should also be involved for a VN user to determine the expected communication data rate and route selection result.

Considering these influencing factors, we propose two route selection schemes: the instantaneous scheme and long-term scheme. In the instantaneous scheme, when making a route selection, the cognitive VN user only considers the immediate traffic intensity to calculate the expected data rate as a comparison metric among different routes. While in the long-term route selection scheme, the dynamic traffic intensity is considered and the long-term expected data rate is derived as the route selection metric. We can see that the instantaneous scheme is more suitable for the VN users who only take a short-distance travel, while the long-term scheme is more appropriate for the VN users who would take a relatively long-distance trip. Note that during the route selection analysis in this section, the cognitive vehicular network throughput is assumed to be known, which will be explicitly analyzed in the next section.

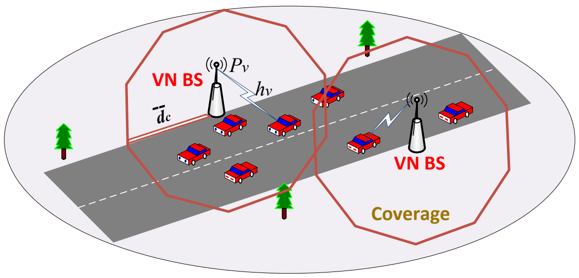

Fig. 4. Coverage radius of VN BSs.

A. Instantaneous Route Selection

In the instantaneous route selection scheme, when confronted with multiple routes from current position to the desired destination, the VN users first evaluate the expected data rate that can be obtained on each route according to the current route conditions. Based on the performance evaluations, they further select the route that can provide highest expected data rate. Suppose there are M routes for selection from position A to position B. Let us denote R_i as the vehicular network throughput on route i, which is determined by the number and locations of TV BSs along route i. The network throughput R_i will be analyzed in the next section. Here, we assume that the VN users who are simultaneously served by the same VN BS share the network resources through Time Division Multiple Access (TDMA) in a centralized way. In such a case, when there are totally Θ VN users sharing the same VN BS, the data rate of each VN user on route i can be simply calculated by

$$U_i(\Theta) = \frac{R_i}{\Theta}. \tag{1}$$

Note that all three parameters in (1) should be function of the route index i and the VN BS index. To simplify the notations, we do not use the VN BS index.

Then, let us see how the traffic intensity affects a VN user's data rate performance. The coverage area of a VN BS is determined by its transmission power and the channel conditions. Here, we use protocol interference model to analyze the VN BS's coverage area. In this model, a transmission is considered successful if and only if the receiving node is within the transmission range of the corresponding transmitting node and is outside the interference range of all non-intended transmitting nodes [41]. Usually, the transmission/interference ranges are assumed as circles, the radius of which depend on the power of transmission/interference node, as well as the channel attenuation. By using the protocol interference model, a data transmission from a VN BS to a VN user is considered successful only if the received power at the VN user exceeds θ ($\theta \geq 1$) times of the noise power σ^2. As shown in Fig. 4, when the transmission power control factor of a VN BS is $P_v (0 \leq P_v \leq 1)$ and the channel realization is h_v, the coverage radius of the VN BS, d_c, can be calculated by

$$\frac{P_v h_v}{d_c^\alpha} = \theta\sigma^2 \ \Rightarrow \ d_c = \left(\frac{P_v h_v}{\theta\sigma^2}\right)^{1/\alpha}, \tag{2}$$

where h_v is the attenuation in power due to fading on the link, the effect of transmission power, antenna gain, etc, σ^2 is the variance of a zero-mean circularly symmetric complex Gaussian noise and α is the path loss exponent. We consider equal power allocation in this paper, which means that the VN BSs equally distribute the transmission power among all the accessible channels. Moreover, we assume that the channel gain h_v are i.i.d over all BSs and obey Rayleigh distribution with mean ϵ_v, i.e.,

$$f_{h_v}(x) = \frac{1}{\epsilon_v} e^{-x/\epsilon_v}. \tag{3}$$

Denote $\{\epsilon_{v,k}\}$ as the set of channel gain, where $\epsilon_{v,k}$ represent the channel gains from VN BS s_v to the user; and k corresponds to the number of walls that the signal goes through. Here, we consider the vehicle body penetration as once penetration and adopt $\epsilon_{v,1}$ as the mean channel gain. Thus, considering the channel statistics, we have the average coverage radius of the VN BS, $\bar{d}_c$, as follows

$$\bar{d}_c = \int_{x=0}^{+\infty} \left(\frac{P_v x}{\theta\sigma^2}\right)^{1/\alpha} \frac{1}{\epsilon_{v,1}} e^{-x/\epsilon_{v,1}} \mathrm{d}x. \tag{4}$$

Since it is assumed that the VN BSs are all deployed just on the roadside to better support vehicular communications, the coverage area of each VN BS can be approximated as $2\bar{d}_c$. Note that the VN users are served by the nearest VN BS. Thus, within the coverage area of a VN BS, the VN users would be served by the same VN BS and the number of them is determined by the traffic intensity. Here, we assume that the traffics on the route i follow the Poisson process with intensity μ_i (the number of vehicles per m), i.e., the distances between two adjacent vehicles are independent and identically distributed with exponential distribution of expectation μ_i^{-1}. Note that μ_i satisfies $0 < \mu_i < 1$ since there cannot be two vehicles within one meter on the road. In this paper, we quantize the traffic intensity into L discrete levels for practical purpose, e.g., Google map also uses different colors to represent different levels of traffic intensity. In such a case, we have

$$\mu_i \in \Psi = \left\{\frac{1}{L}, \frac{2}{L}, ..., \frac{L-1}{L}\right\}. \tag{5}$$

Based on the current traffic intensity μ_i, we can have the average number of VN users that simultaneously share the same VN BS on route i as

$$\Theta_i = 2\rho\mu_i\bar{d}_c, \tag{6}$$

where $2\bar{d}_c$ is the covered road length of one VN BS and $2\bar{d}_c\mu_i$ is the total number of users in the coverage of one VN BS, ρ represents the percentage of VN users among all vehicles and we assume that on average there is at most one VN user in each vehicle. In such a case, the average data rate that can be obtained by each VN user can be calculated as follows

$$U_i(\mu_i) = \frac{R_i}{2\rho\mu_i\bar{d}_c}. \tag{7}$$

Thus, the VN user can first calculate and compare the average data rates of all M routes through (7) using the TV BSs intensity and current traffic intensity of each route $\{\mu_i\}$, and then select the route with highest data rate, i.e., $\arg\max_{1\leq i\leq M} U_i(\mu_i)$.

B. Long-term Route Selection

Once a VN user selects a route, he/she would drive on the route for a short period of time, during which the traffic situation may change. Considering such a circumstance, we propose the long-term route selection scheme. In this scheme, when evaluating the expected data rates of different routes, the VN users not only consider the route conditions in current time instant, but also take into account the dynamic changes of route conditions in the near future. As aforementioned, the route conditions include both TV BSs intensity along the route and the traffic intensity of the route. Since the locations of TV BSs are static, we only consider the dynamic changes of traffic intensity. Considering that the traffic intensity in current time instant is only related with that in the last time instant, we can regard the dynamic traffic intensity on route i, $\{\mu_i^{(1)}, \mu_i^{(2)}, ..., \mu_i^{(t)}, ...\}$, as a Markov process, where the superscript (t) represents the time instant. As discussed in the previous subsetion, the traffic intensity μ_i is quantized into L levels. In such a case, we can define the discrete traffic intensity $\mu_i \in \Psi = \{\frac{1}{L}, \frac{2}{L}, ..., \frac{L-1}{L}\}$ as the traffic state of route i and model the state transition probability as follows

$$\mathbb{P}\left(\mu_i^{(t+1)} = \frac{j-1}{L}\middle|\mu_i^{(t)} = \frac{j}{L}\right) = \phi_j^-, \tag{8}$$

$$\mathbb{P}\left(\mu_i^{(t+1)} = \frac{j+1}{L}\middle|\mu_i^{(t)} = \frac{j}{L}\right) = \phi_j^+, \tag{9}$$

$$\mathbb{P}\left(\mu_i^{(t+1)} = \frac{j}{L}\middle|\mu_i^{(t)} = \frac{j}{L}\right) = 1 - \phi_j^- - \phi_j^+. \tag{10}$$

where we only consider that the transitions between the adjacent states since the dynamic changing of traffic intensity on a road should be a gradual process.

When a VN user is determining the route selection and evaluating the expected data rate of each route, he/she only has the knowledge of current traffic states of all possible routes, $\{\mu_1^{(0)}, \mu_2^{(0)}, ..., \mu_M^{(0)}\}$. The question is how to incorporate the traffic state changes in the near future into the data rate evaluation of each route. We find that this is quite similar to a Markov Decision Process (MDP) problem [42], where a user's optimal decision can be obtained by maximizing the user's long-term expected utility described by the concept of "Bellman equation". The difference is that, in a MDP model, the user can re-optimize his/her decision when the system state changes; while in the route selection problem, once the VN user selects and drives on a route, changing the route may not be cost-effective, especially on the inter-city highway. In the MDP model, Bellman equation is used to describe a user's long-term expected utility, which contains both the immediate utility of current state and the expected utilities in the near future. Considering the special characteristic of the route selection problem and according to the fundamental concept of Bellman equation, we can define a VN user's expected data rate on route i when the initial traffic state is μ_i by

$$V_i(\mu_i) = U_i(\mu_i) + \beta \sum_{\mu_i' \in \Psi} \mathbb{P}(\mu_i'|\mu_i) V_i(\mu_i'), \tag{11}$$

where $V_i(\mu_i)$ represents the long-term expected data rate of route i with initial traffic state μ_i, $U_i(\mu_i)$ as defined in (7) and $\mathbb{P}(\mu_i'|\mu_i)$ is defined in (8-10), β is a discounting factor which ensures the summation is bounded, which can be constant value or a function of travel distance. Note that (10) considers the infinite time with discounting factor and the long-term expected data rate $V_i(\mu_i)$ is not related with the travelling time. Since μ_i is discrete and $\mu_i \in \Psi = \{\frac{1}{L}, \frac{2}{L}, ..., \frac{L-1}{L}\}$, we can define a long-term data rate vector of route i that includes the long-term expected data rates associated with all the possible initial traffic states as follows

$$\mathbf{V}_i = \left[V_i\left(\frac{1}{L}\right), V_i\left(\frac{2}{L}\right), ..., V_i\left(\frac{L-1}{L}\right)\right]. \tag{12}$$

Meanwhile, we can define a immediate data rate vector of route i that includes the immediate expected data rates associated with all the possible initial traffic states as follows

$$\mathbf{U}_i = \left[U_i\left(\frac{1}{L}\right), U_i\left(\frac{2}{L}\right), ..., U_i\left(\frac{L-1}{L}\right)\right]. \tag{13}$$

Thus, we can re-write (11) as

$$\mathbf{V}_i = \mathbf{U}_i + \beta \mathbf{V}_i \mathbf{P}, \tag{14}$$

where $\mathbf{P}$ is the state transition matrix that can be calculated by (8-10). By solving (14), we have

$$\mathbf{V}_i = \mathbf{U}_i (\mathbf{I} - \beta \mathbf{P})^{-1}, \tag{15}$$

where $\mathbf{I}$ is the identity matrix. Therefore, we can obtain the long-term expected data rates of all possible routes with all possible initial traffic states, i.e., $\{\mathbf{V}_1, \mathbf{V}_2, ..., \mathbf{V}_M\}$. Suppose the current traffic states of all routes are $\{\mu_1, \mu_2, ..., \mu_M\}$, the optimal route should be the one with highest long-term expected data rate, i.e., $\arg\max\{V_1(\mu_1), V_2(\mu_2), ..., V_M(\mu_M)\}$. Note the optimal route may attract a lot of users, which leads to the change of the traffic intensity of different route and thus has impact on the throughput. This problem can be resolved by combining the real time traffic intensity into the dynamic traffic intensity prediction model.

IV. Vehicular Network Throughput Analysis

In this section, we analyze the vehicular network throughput on each route, R_i, with the system model shown in Fig. 1. The TV users and VN users are served by the nearest TV BS and VN BS, respectively. Suppose there are N independent licensed TV channels with bandwidth B for each channel. For example, in the United States, there are 50 TV channels numbered 2 through 51, each with 6 MHz bandwidth, approximately lying between 54 and 700 MHz within VHF and UHF bands [43]. In this section, we study two widely accepted spectrum sharing models: overlay model and underlay model [44]. In the spectrum overlay model, the VN BSs can only utilize the channels that are not occupied by the nearby TV BSs. While in the spectrum underlay model, the VN can operate on all N primary channels simultaneously but under strict transmission power constraints. In this paper, we assume that the hand-over process between VN BSs has been handled by the existing works as in [45].

The TV BSs includes various kinds of entities, e.g., terrestrial TV stations and TV translators, Broadcast Auxiliary Service (BAS) links, PLMRS/CMRS (Private Land/Commercial

Mobile Radio Services) base station operations, etc [14]. Overall, the locations of those TV BSs tend to be random, especially when it comes to the consumer deployed PLMRS base stations. In this paper, we assume that the locations of the TV BSs follow a Poisson Point Process (PPP) on the plane with intensity λ (the number of TV BSs per m^2). Note that λ satisfies $0 < \lambda < 1$ since there cannot be two TV BSs within one square meter. The PPP has been widely adopted to model the distribution of fully random placements, e.g., the femtocell BSs [46]. Based on the PPP model, the number of TV BSs in any finite region r, M_r, is Poisson distributed with mean λA_r, i.e.,

$$P(M_r = m) = \frac{e^{-\lambda A_r}(\lambda A_r)^m}{m!}, \tag{16}$$

where A_r is the area of the region r. Note that the intensities (densities) of the TV BSs in different regions can be different, e.g., the intensity in downtown regions would be much higher than that in suburb regions. In the VN application scenario, the intensity of TV BSs around the local street would be much higher than that around the highway. For the VN BSs, we assume that they are deployed near the road in order to better support the vehicular communications, as shown in the zoom-in subfigure of Fig. 1.

In our model, both TV and vehicular networks are based on the single antenna system. The received power per channel at a user located at a distance of d_t from a TV BS s_t is given by,

$$y_t = \frac{h_t}{d_t^{\alpha}} + \sigma^2, \tag{17}$$

where h_t is the realization of the channel. Meanwhile, the receiver power per channel at a user located d_v from a VN BS s_v is given by,

$$y_v = \frac{P_v h_v}{d_v^{\alpha}} + \sigma^2, \tag{18}$$

where P_v is the power control factor. Note that the power control is fulfilled by VN BS. In the spectrum overlay model, since the VN BSs only utilize the vacant primary channels, they can adopt high transmission power as long as the inter-cell interference is moderate, while in the spectrum underlay model, to maintain the QoS of the TV network, the VN BSs should carefully control the transmission power to meet the interference requirement. We assume that the channel gain $\{h_t\}$ are i.i.d over all BSs and obey Rayleigh distribution with mean ϵ_t, i.e.,

$$f_{h_t}(x) = \frac{1}{\epsilon_t} e^{-x/\epsilon_t}. \tag{19}$$

Denote $\{\epsilon_{t,k}\}$ as the set of channel gain, where $\epsilon_{t,k}$ represent the channel gains from TV BS s_t to the user; and k corresponds to the number of walls that the signal goes through.

In the following, we will theoretically analyze the vehicular network throughput under two spectrum sharing models based on the aforementioned system model. On one hand, for the spectrum overlay model, since the VN BSs can only utilize the unoccupied channels, the total accessible bandwidth is limited, but the transmission power is not strictly constrained. On the other hand, for the spectrum underlay model, although the transmission power should be strictly controlled to guarantee the TV network performance, the VN BSs can access the whole TV bands simultaneously. Therefore, we can see that there are both advantages and disadvantages for these two models and we will compare the performances of them in the experiment. Note that in the following network throughput analysis, we only focus on the downlink throughput for a single VN user.

A. Spectrum Overlay Model

In the spectrum overlay model, the vehicular network can only access the channels that are not occupied by the nearby TV BSs. The unoccupied channels information can be obtained by spectrum sensing function or querying Google white space database [14], where Google maintains the real-time unoccupied channels information of all the locations in the United States. Since the VN BSs can only utilize the unoccupied channels, we need to first study the maximum number of channels that a VN BS can utilize in order to analyze the vehicular network throughput. According to Google TV station database [14], each TV BS only constantly occupies one TV channel and adjacent TV BSs utilize different channels to avoid interference. In such a case, the number of unoccupied channels is determined by the number of nearby TV BSs that could be interfered by a VN BS, which is closely related by the TV BS's keep-out radius and the VN BS's interference radius. The keep-out radius d_k, defined in the IEEE 802.22 standard, is used to protect the PUs in the spatial domain, within which the secondary network cannot be deployed [47]. The interference radius d_f of a VN BS depends on the VN BS's transmission power. In such a case, according to the PPP model, the expected number of nearby TV BSs can be calculated by $\lambda\pi(d_k + d_f)^2$, and the expected number of channels that can be utilized by the VN BS can be calculated as follow

$$N_a = N - \lambda\pi(d_k + d_f)^2, \tag{20}$$

where N is the total number of TV channels, d_k is a constant predetermined by the specifications of TV networks and d_f will be analyzed in the following.

Suppose the interference range of a VN BS is with radius d_f. Then, the interference area should be πd_f^2, which means that the VN BS cannot utilize the channels that are occupied by the TV BSs inside the interference area. Here, we have a trade-off problem in terms of configuring the VN BS's transmission power. On one hand, the higher transmission power adopted by the VN BS, the higher achievable throughput of each accessible channel can be obtained by the VN BS. On the other hand, the higher transmission power can also lead to a wider interference range, which increases the number of protected TV BSs and decreases the number of accessible primary channels. Therefore, the VN BS's transmission power should be appropriately configured in order to maximize the vehicular network throughput. As aforementioned, the interference range of a VN BS is proportional to its transmission power control factor P_v. According to the protocol interference model [41], an interference power from a VN BS is considered non-negligible for the TV users only if it exceeds $1/\theta$ ($\theta \geq 1$) times of the noise power σ^2 on the link. Thus, similar to the calculation of coverage radius in (2), when the transmission power of a VN BS is P_v, the interference radius d_f can be calculated by

$$\frac{P_v h_v}{d_f^{\alpha}} = \frac{\sigma^2}{\theta} \;\Rightarrow\; d_f = \left(\frac{\theta P_v h_v}{\sigma^2}\right)^{1/\alpha}. \tag{21}$$

In such a case, according to (20), we can have the expected number of channels that can be utilized by the VN BS as follows

$$N_a = N - \lambda\pi\left[d_k + \left(\frac{\theta P_v h_v}{\sigma^2}\right)^{1/\alpha}\right]^2. \tag{22}$$

Since the VN BSs only utilize the vacant channels, there is no interference power from the TV BSs for the VN users. Moreover, since the VN BSs are just deployed near the road with limited coverage area, the inter-cell interference among VN BSs is negligible and not considered. In such a case, the signal-noise-ratio (SNR) of the VN user is $\frac{P_v h_v}{d_{v,v}^{\alpha}\sigma^2}$, and thus, the achievable downlink throughput per channel of one channel realization can be given by

$$R_{vp} = B\log\left(1 + \frac{P_v h_v}{d_{v,v}^{\alpha}\sigma^2}\right). \tag{23}$$

Combining (22) and (23), we can have the total expected downlink throughput of the vehicular network under spectrum overlay model as follows

$$R_v^{\mathrm{OL}} = B\int_{x=0}^{+\infty}\left(N - \lambda\pi\left[d_k + \left(\frac{\theta P_v x}{\sigma^2}\right)^{1/\alpha}\right]^2\right) \log\left(1 + \frac{P_v x}{d_{v,v}^{\alpha}\sigma^2}\right) f_{h_v}(x)\mathrm{d}x. \tag{24}$$

In such a case, the optimal transmission power control factor can be found by solving the following maximization problem

$$\begin{aligned} \arg\max_{P_v} \quad & B\int_{x=0}^{+\infty}\left(N - \lambda\pi\left[d_k + \left(\frac{\theta P_v x}{\sigma^2}\right)^{1/\alpha}\right]^2\right) \log\left(1 + \frac{P_v x}{d_{v,v}^{\alpha}\sigma^2}\right)\frac{1}{\epsilon_{v,1}}e^{-x/\epsilon_{v,1}}\mathrm{d}x, \\ \text{s.t.} \quad & 0 \le P_v \le 1. \end{aligned} \tag{25}$$

The gradient descent method can be used to solve the above optimization problem in (25). Then, by substituting the optimal transmission power control factor P_v back into (23), we can have the optimal vehicular network throughput under the spectrum overlay model.

B. Spectrum Underlay Model

In the spectrum underlay model, the vehicular network can access all N primary channels simultaneously as long as the QoS of the TV network is guaranteed. The advantage of this model is that the VN BSs and users do not need to perform spectrum sensing or querying the white space database as in the spectrum overlay model, while the disadvantage is that they need to strictly control their transmission power. In this paper, we regard the converge probability as the metric of TV network's QoS, which is the probability that the signal-to-interference-plus-noise (SINR) at any network user is higher than an outage threshold. The coverage probability is also the complementary cumulative distribution function (CCDF) of SINR. In the following, we will first analyze the coverage probability of TV network users and then derive the optimal transmission power control factor for the VN BSs.

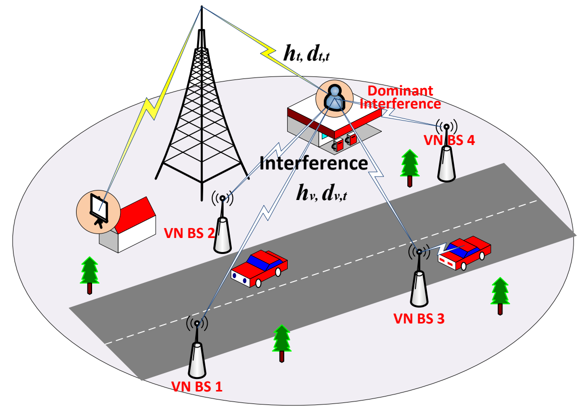

Fig. 5. Coverage radius of VN BSs.

1) Coverage Probability of TV Users: As shown in Fig. 5, let us denote $d_{t,t}$ and h_t as the distance and channel gain between the TV user and the nearest TV BS (the serving TV BS), respectively; denote $d_{v_i,t}$ and h_{v_i} as the distance and channel gain between the TV user and the VN BS b_{v_i}, respectively; denote $\Phi_v = \{b_{v_i}\}$ as the set of all VN BSs near the TV user. Thus, the received TV signal power of the TV user is $h_t d_{t,t}^{-\alpha}$, and its SINR can be given by

$$\gamma_t = \frac{h_t d_{t,t}^{-\alpha}}{\Lambda}, \tag{26}$$

where Λ represents the interference from nearby VN BSs plus channel noise. Note that there is no inter-cell interference among the TV BSs since each TV BS only occupies one TV channel and adjacent TV BSs utilize different channels to avoid interference according to Google TV station database [14]. For the TV user, there exists a dominant interfering VN BS, i.e., the nearest VN BS b_{v_0} located d_{v_0} from the TV user. In such a case, the interference plus noise Λ can be calculated as follows

$$\Lambda = P_{v_0}h_{v_0}d_{v_0,t}^{-\alpha} + \sum_{b_{v_i}\in\Phi_v\backslash b_{v_0}} P_{v_i}h_{v_i}d_{v_i,t}^{-\alpha} + \sigma^2, \tag{27}$$

where the first term in the RHS of (27) is the dominant interference from the nearest VN BS b_{v_0}, the second term represents the interference from all other VN BSs except b_{v_0}, σ^2 stands for the variance of channel noise and P_{v_i} is the transmission power control factor of the VN BS b_{v_i}. In such a case, we can have the SINR of the TV user as

$$\gamma_t = \frac{h_t d_{t,t}^{-\alpha}}{P_{v_0}h_{v_0}d_{v_0,t}^{-\alpha} + \sum_{b_{v_i}\in\Phi_v\backslash b_{v_0}} P_{v_i}h_{v_i}d_{v_i,t}^{-\alpha} + \sigma^2}. \tag{28}$$

Suppose the SINR of the TV user should be at least larger than a threshold Γ, i.e., the target SINR, the coverage probability of the TV network can be defined by

$$\mathbb{P}_c = \mathbb{P}\left[\text{SINR is larger than } \Gamma\right] = \mathbb{E}\left[\mathbb{P}\left(\gamma_t \geq \Gamma\right)\right]. \quad (29)$$

The following theorem gives the expression of the coverage probability of the TV network.

Theorem 1: In a heterogenous network with a primary TV network and cognitive vehicular network, the coverage probability of a TV user is

$$\mathbb{P}_c = 2\pi\lambda \int_{d_{t,t}=0}^{+\infty} \frac{\exp\left(-\frac{d_{t,t}^{\alpha}\sigma^2\Gamma}{\epsilon_t}\right)}{1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_0,t}^{-\alpha} P_{v_0}\Gamma}{\epsilon_t}} \prod_{b_{v_i}\in\Phi_v\setminus b_{v_0}} \frac{1}{1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_i,t}^{-\alpha}P_{v_i}\Gamma}{\epsilon_t}} d_{t,t} e^{-\lambda\pi d_{t,t}^2} \mathrm{d}d_{t,t}. \quad (30)$$

Proof: Since the TV user is served by the nearest TV BS, no BS can be closer than $d_{t,t}$. Thus, according to (16), the cumulative distribution function (CDF) of d_t can be derived as follows

$$\begin{aligned}\mathbb{P}(d_{t,t} \leq D) &= 1 - \mathbb{P}(d_{t,t} > D)\\ &= 1 - \mathbb{P}[\text{No TV BS in the area } \pi D^2]\\ &= 1 - e^{-\lambda\pi D^2},\end{aligned} \quad (31)$$

and the probability density function (PDF) can be written as

$$f_{d_{t,t}}(d_{t,t}) = \frac{\mathrm{d}\left(1-e^{-\lambda\pi d_{t,t}^2}\right)}{\mathrm{d}d_{t,t}} = 2\pi\lambda d_{t,t} e^{-\lambda\pi d_{t,t}^2} \quad (32)$$

Suppose the SINR of the TV user should be at least larger than a threshold Γ, the coverage probability of it can be calculated by

$$\begin{aligned}\mathbb{P}_c &= \int_{d_{t,t}=0}^{+\infty} \mathbb{P}\left[\gamma_t \geq \Gamma\right] f_{d_{t,t}}(d_{t,t})\mathrm{d}d_{t,t}\\ &= \int_0^{+\infty} \mathbb{P}\left[\frac{h_t d_{t,t}^{-\alpha}}{\Lambda} \geq \Gamma\right] 2\pi\lambda d_{t,t} e^{-\lambda\pi d_{t,t}^2}\mathrm{d}d_{t,t}\\ &= \int_{d_{t,t}=0}^{+\infty} \mathbb{P}\left[h_t \geq d_{t,t}^{\alpha}\Gamma\Lambda\right] 2\pi\lambda d_{t,t} e^{-\lambda\pi d_{t,t}^2}\mathrm{d}d_{t,t}.\end{aligned} \quad (33)$$

Note that the channel gain h_t obeys Rayleigh distribution, thus we have

$$\begin{aligned}\mathbb{P}\left[h_t \geq d_{t,t}^{\alpha}\Gamma\Lambda\right] &= \mathbb{E}_{\Lambda}\left[\int_{d_{t,t}^{\alpha}\Gamma\Lambda}^{+\infty} \frac{1}{\epsilon_t} e^{-x/\epsilon_t}\mathrm{d}x\right]\\ &= \mathbb{E}_{\Lambda}\left[\exp\left(-\frac{d_{t,t}^{\alpha}\Gamma}{\epsilon_t}\Lambda\right)\right]\\ &= \mathcal{L}_{\Lambda}\left(\frac{d_{t,t}^{\alpha}\Gamma}{\epsilon_t}\right),\end{aligned} \quad (34)$$

where $\mathcal{L}_{\Lambda}(.)$ represents the Laplace transform of the interference plus noise of the TV user, Λ; and ϵ_t can be $\epsilon_{t,0}$ for outdoor TV user or $\epsilon_{t,1}$ for indoor TV user. The Laplace transform of Λ can be calculated as follows

$$\begin{aligned}\mathcal{L}_{\Lambda}(s) &= \mathbb{E}_{\Lambda}\left[e^{-s\Lambda}\right]\\ &= \mathbb{E}_{\Lambda}\left[e^{-s\sigma^2} e^{-sP_{v_0}h_{v_0}d_{v_0,t}^{-\alpha}} \prod_{b_{v_i}\in\Phi_v\setminus b_{v_0}} e^{-sP_{v_i}h_{v_i}d_{v_i,t}^{-\alpha}}\right].\end{aligned} \quad (35)$$

Since all the channel gains $\{h_{v_i}\}$ obey the Raleigh distribution and are independent of each other, the (35) can be re-written as

$$\begin{aligned}\mathcal{L}_{\Lambda}(s) &= e^{-s\sigma^2}\mathbb{E}_{h_{v_0}}\left[e^{-sP_{v_0}h_{v_0}d_{v_0,t}^{-\alpha}}\right] \cdot \prod_{b_{v_i}\in\Phi_v\setminus b_{v_0}} \mathbb{E}_{h_{v_i}}\left[e^{-sP_{v_i}h_{v_i}d_{v_i,t}^{-\alpha}}\right]\\ &= \frac{e^{-s\sigma^2}}{1+sP_{v_0}\epsilon_v d_{v_0,t}^{-\alpha}} \prod_{b_{v_i}\in\Phi_v\setminus b_{v_0}} \frac{1}{1+sP_{v_i}\epsilon_v d_{v_i,t}^{-\alpha}},\end{aligned} \quad (36)$$

where ϵ_v can be $\epsilon_{v,0}$ for outdoor TV user or $\epsilon_{v,1}$ for indoor TV user.

Thus, by substituting $s = \frac{d_t^{\alpha}\Gamma}{\epsilon_t}$ into (34) and then substitute (34) into (33), we have

$$\begin{aligned}\mathbb{P}_c &= \int_{d_{t,t}=0}^{+\infty} \mathcal{L}_{\Lambda}\left(\frac{d_{t,t}^{\alpha}\Gamma}{\epsilon_t}\right) 2\pi\lambda d_{t,t} e^{-\lambda\pi d_{t,t}^2}\mathrm{d}d_{t,t}\\ &= 2\pi\lambda \int_{d_{t,t}=0}^{+\infty} \frac{\exp\left(-\frac{d_{t,t}^{\alpha}\sigma^2\Gamma}{\epsilon_t}\right)}{1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_0,t}^{-\alpha}P_{v_0}\Gamma}{\epsilon_t}} \prod_{b_{v_i}\in\Phi_v\setminus b_{v_0}} \frac{1}{1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_i,t}^{-\alpha}P_{v_i}\Gamma}{\epsilon_t}} d_{t,t}e^{-\lambda\pi d_{t,t}^2}\mathrm{d}d_{t,t},\end{aligned} \quad (37)$$

which complete the proof of the theorem. ■

Remark: From the expression of the coverage probability in (37), we can see that there are three main terms: $\exp\left(-\frac{d_{t,t}^{\alpha}\sigma^2\Gamma}{\epsilon_t}\right)$ is corresponding to the channel noise, $1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_0,t}^{-\alpha}P_{v_0}\Gamma}{\epsilon_t}$ is corresponding to the dominant interference from the nearest VN BS, and the $\prod$ term with $1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_i,t}^{-\alpha}P_{v_i}\Gamma}{\epsilon_t}$ is corresponding to the interference from all other VN BSs. As discussed in the system model, the VN BSs are assumed to be deployed near the road in order to better support the vehicular communication performance, and a VN BS is supposed to only serve the vehicles on the road instead of covering a wide area. In such a case, for the TV user, compared with the dominant interference from the nearest VN BS, the interference from other VN BSs can be negligible. Furthermore, considering that the noise is also much smaller than the interference, the coverage probability in (37) can be approximated by

$$\begin{aligned}\mathbb{P}_c &\approx 2\pi\lambda \int_{d_{t,t}=0}^{+\infty} \frac{d_{t,t}e^{-\lambda\pi d_{t,t}^2}}{1+\frac{d_{t,t}^{\alpha}\epsilon_v d_{v_0,t}^{-\alpha}P_{v_0}\Gamma}{\epsilon_t}}\mathrm{d}d_{t,t}\\ &= \pi\lambda \int_{x=0}^{+\infty} \frac{\epsilon_t x^{-2/\alpha} e^{-\lambda\pi x}}{\epsilon_t x^{-2/\alpha} + \epsilon_v \bar{d}_{v,t}^{-\alpha}\Gamma P_v}\mathrm{d}x,\end{aligned} \quad (38)$$

where the second equality is obtained by substituting x for $d_{t,t}^2$, replacing P_{v_0} with P_v as the general transmission power control factor of the VN BSs and replacing $d_{v_0,t}$ with $\bar{d}_{v,t}$ as the average distance between the TV users and the nearest VN BS. Based on the coverage probability analysis, we can further study how to control the VN BS's downlink transmission power P_v. Note that in the following power control analysis, we will use the approximated coverage probability in (38) for simplicity and verify the difference due to the approximation in the simulation subsection.

2) Power Control of VN BSs: In the spectrum underlay model, although the vehicular network can access all N primary channels, they may also suffer from the interference from the TV BSs. In such a case, the SINR of the VN users can be written by

$$\gamma_v = \frac{P_v h_v d_{v,v}^{-\alpha}}{I_t + \sigma^2}, \tag{39}$$

where $d_{v,v}$ denotes the distance between the VN user and the nearest VN BS, and I_t represents the interference from the TV BSs in one primary channel. Similarly to the approximation of the coverage probability in the previous subsection, we only consider the dominant interference from the nearest TV BSs. Since each TV BS only occupies one primary channel [14], the interference from each primary channel is considered from the nearest TV BS that occupies the dedicated channel. Thus, I_t represents the dedicated channel interference, which is considered as the same for all primary channels due to the independence and homogeneity of the primary channels. Suppose that in a dedicated channel, the distance between the nearest TV BS occupying that channel and the VN user is $d_{t,v}$, according to (32), the PDF of $d_{t,v}$ can be given as

$$f_{d_{t,v}}(d_{t,v}) = 2\pi \frac{\lambda}{N} d_{t,v} e^{-\frac{\lambda}{N}\pi d_{t,v}^2}, \tag{40}$$

where the intensity of the TV BSs occupying some dedicated channel is regarded as $\frac{\lambda}{N}$ since the total intensity is λ and the number of channels is N. This is based on the assumption that the primary channels are uniformly occupied by the TV BSs, which is reasonable since the neighboring TV BSs are configured to operate on different channels to avoid inter-cell interference and all the channels are occupied with approximately equal probability. Thus, the dedicated channel interference I_t can be calculated as follows

$$\begin{aligned} I_t &= \int_{x=0}^{+\infty} \int_{d_{t,v}=d_k}^{+\infty} \frac{x}{d_{t,v}^{\alpha}} f_{d_{t,v}}(d_{t,v}) f_{h_t}(x) \mathrm{d}d_{t,v} \mathrm{d}x \\ &= \frac{2\pi\lambda}{\epsilon_{t,1} N} \int_{x=0}^{+\infty} x e^{-x/\epsilon_{t,1}} \mathrm{d}x \int_{d_{t,v}=d_k}^{+\infty} \frac{1}{d_{t,v}^{\alpha}} d_{t,v} e^{-\frac{\lambda}{N}\pi d_{t,v}^2} \mathrm{d}d_{t,v} \\ &= \frac{2\pi\lambda\epsilon_{t,1}}{N} \int_{d_{t,v}=d_k}^{+\infty} \frac{1}{d_{t,v}^{\alpha-1}} e^{-\frac{\lambda}{N}\pi d_{t,v}^2} \mathrm{d}d_{t,v}, \end{aligned} \tag{41}$$

where d_k is the keep-out radius.

By substituting (41) into (39), we can calculate the SINR of the VN users. Based on the SINR, we can further obtain the expected downlink throughput of the vehicular network under the spectrum underlay model as follows

$$R_v^{\text{UL}} = BN \int_{x=0}^{+\infty} \log\left(1 + \frac{P_v x d_{v,v}^{-\alpha}}{I_t + \sigma^2}\right) f_{h_v}(x) \mathrm{d}x. \tag{42}$$

Denoting $\mathbb{P}_{th}$ as the threshold coverage probability, we can have the following optimization problem for finding the VN BS's optimal power control factor P_v,

$$\begin{aligned} \arg\max_{P_v} \quad & BN \int_{x=0}^{+\infty} \log\left(1 + \frac{P_v x d_{v,v}^{-\alpha}}{I_t + \sigma^2}\right) \frac{1}{\epsilon_{v,1}} e^{-x/\epsilon_{v,1}} \mathrm{d}x, \\ \text{s.t.} \quad & \mathbb{P}_c = \pi\lambda \int_{x=0}^{+\infty} \frac{\epsilon_t x^{-2/\alpha} e^{-\lambda\pi x}}{\epsilon_t x^{-2/\alpha} + \epsilon_v \bar{d}_{v,t}^{-\alpha} \Gamma P_v} \mathrm{d}x \geq \mathbb{P}_{th}, \\ & 0 \leq P_v \leq 1. \end{aligned} \tag{43}$$

TABLE I
NUMERICAL PARAMETERS FOR PERFORMANCE EVALUATION.

Parameter	Value
Max Tx Power	50 dBm (TV BS), 30 dBm (VN BS)
Antennas	1Tx, 1Rx (both TV network and VN)
Antennas gains	20 dB (TV BS), 5 dB (VN BS)
Path loss exponent	$\alpha = 3$
Path	10 dB + $10\alpha \log_{10}(r)$, r in meter
Penetration loss	5 dB
Noise power	$\sigma^2 = 0.1$ dB
Protocol interference parameter	$\theta = 10$
Target SINR	$\Gamma = 3$ dB
Minimum coverage probability	$\mathbb{P}_{th} = 0.9$

where the objective function is the VN users' expected downlink throughput R_v^{UL} and the constraint is the TV users' coverage probability requirement, i.e., the interference control. We can see that the objective function is an increasing function in terms of the VN BS's transmission power P_v, i.e., the higher transmission power can lead to the higher SINR, as well as the higher throughput. On the other hand, the constraint in (43) is a decreasing function in terms of the VN BS's transmission power P_v, i.e., the higher transmission power of the VN BS leads to the higher interference and lower coverage probability of TV users. Therefore, given the minimum coverage probability required by the TV users, the maximum acceptable transmission power of the VN BS can be easily found.

V. EXPERIMENT RESULTS

A. Network Throughput Evaluation

In this subsection, we evaluate the network throughput performance for both spectrum overlay and underlay models with the simulation setting described as follows. The number of TV channels N is set to be 50 since there are 50 TV channels numbered 2 to 51 according to the United States frequency allocation chart [43]. While the Federal Communications Commission (FCC) defines that the keep-out radius of each TV BS ranges from 28.3 km to 91.8 km [48], we set the keep-out radius d_k to be 40 km in our simulations. The number of TV BSs is randomly generated according to Poisson distribution with a certain intensity which will be specified in the simulations, and the locations of these BSs are assumed to be uniformly distributed in the observed area. The average distance between the TV user and the nearest VN BS, $\bar{d}_{v,t}$, is set as 10 meters and the distances between the TV user and other VN BSs, $d_{v_i,t}$, are set randomly between 50 meters to 100 meters. The related parameters for the channel model are listed in Table I, where the transmission power and the path loss model are set according to [49].

We first illustrate the VN's expected downlink throughput performance of the spectrum overlay model in Fig. 6, which is obtained by solving the maximization problem in (25). The throughput performance is evaluated under different distances $d_{v,v}$ between the VN BS and the VN user, as well as different intensities λ of the TV BSs. From Fig. 6, we can see that the expected downlink throughput R_v^{OL} decreases with the increase of $d_{v,v}$ due to the large-scale path loss. Meanwhile, R_v^{UL} also decreases with the increase of the TV BSs' intensity λ. This

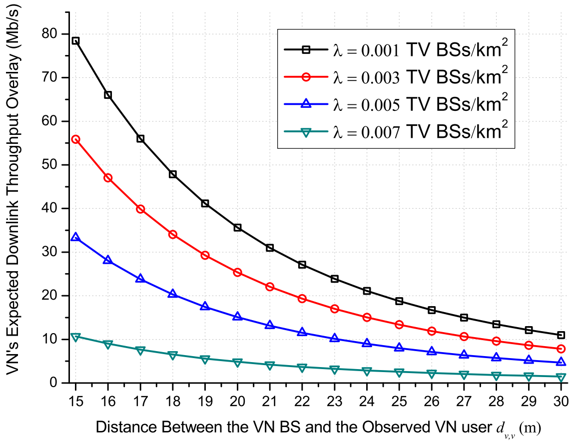

Fig. 6. VN network performance under spectrum overlay model.

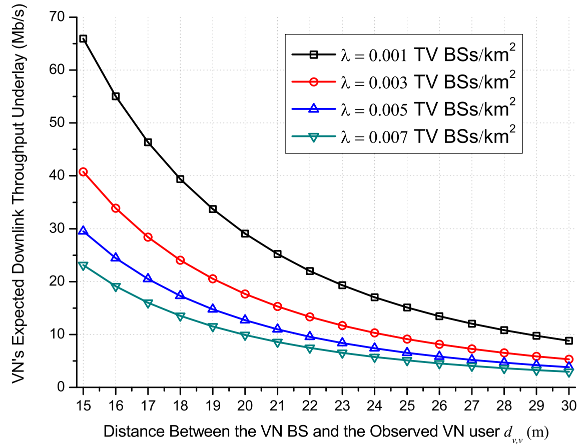

Fig. 8. VN network performance under spectrum underlay model.

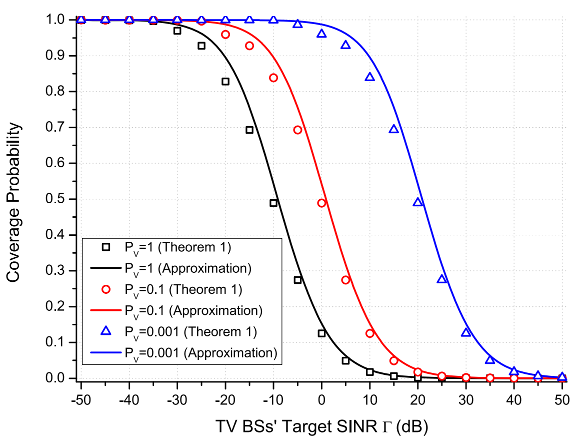

Fig. 7. VN network coverage probability under spectrum underlay model.

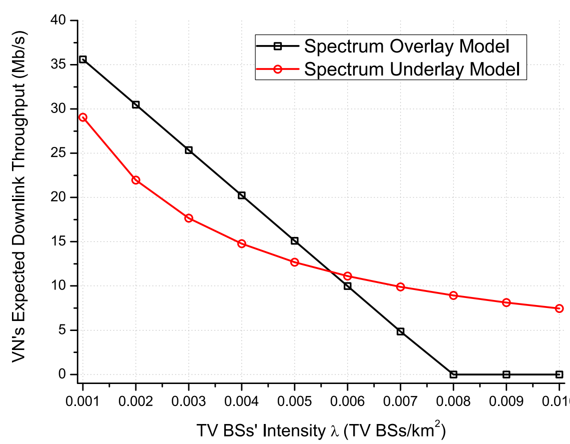

Fig. 9. Performance comparison between spectrum overlay and underlay.

is because the more TV BSs are located nearby the VN BS, the fewer unoccupied channels that can be utilized by the VN BS, which leads to the less available bandwidth and less throughput for the vehicular network.

We then illustrate the VN's expected downlink throughput performance of the spectrum underlay model. Fig. 7 shows the coverage probability performance under different target SINRs and different transmission power control factors P_v of the VN BS, where all the VN BSs adopt the same P_v. In the figure, the Theorem 1 results are obtained by (30), while the approximated results are obtained by (38). We can see that both results are close to each other since the interference from other VN BSs are negligible compared with that from the nearest VN BS due to the VN BS's low transmission power and long-distance path loss. Since the coverage probability $\mathbb{P}_c$ is the complementary CDF of SINR, we can see that when the target SINR increases, $\mathbb{P}_c$ decreases. In addition, as the VN BS's transmission power increases, the interference to the TV users increases, which leads to the decrease of the coverage probability. Based on the coverage probability analysis, we calculate the VN's expected downlink throughput by solving the maximization problem in (43) and show the performance in Fig. 8. Similar to Fig. 6, the throughput performance under underlay spectrum model is also evaluated under different VN BS-VN users distances $d_{v,v}$ and different TV BSs intensities λ. We can see that the phenomenon is also similar to that of the overlay spectrum model, i.e., R_v^{UL} is also a decreasing function in terms of both $d_{v,v}$ and λ.

To compare the performances of the spectrum overlay and underlay models, we also illustrate the expected downlink throughput under different TV BSs' intensities λ in Fig. 9, where the average distance between the VN user and the nearest VN BS is set as $d_{v,v} = 20$ meters. As discussed above, both of them decrease as the increase of intensity λ due to the decrease of the TV white space opportunities. We can see from the figure that when the TV BSs' intensity λ is relatively small, the performance of the spectrum overlay is better than that of the spectrum underlay. This is because when the intensity λ is small, there are many unoccupied TV channels that can be fully utilized by the overlay model with relatively higher transmission power. For the underlay model, since the occupied and unoccupied channels cannot be distinguished, only limited transmission power can be used, which leads to worse throughput performance. When the TV BSs' intensity λ becomes larger, we can see that the spectrum underlay outperforms spectrum overlay. Since the VN BSs can only utilize the unoccupied channels under the overlay model, there exists a threshold $\lambda_{th} = 0.008$ above which no channel is available and thus no throughput can be obtained.

Which model is more appropriate for the current situations

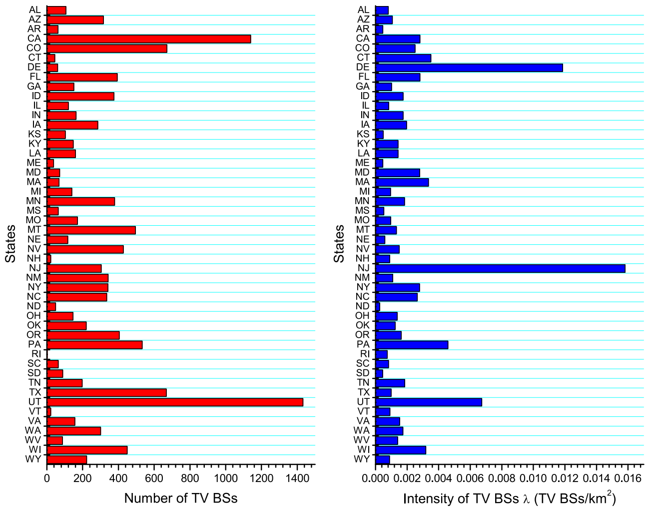

Fig. 10. Number and intensity of TV BSs in each state.

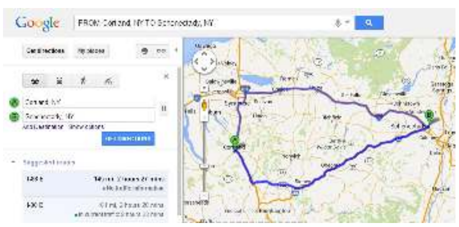

Fig. 11. Google map between Cortland and Schenectady in New York State.

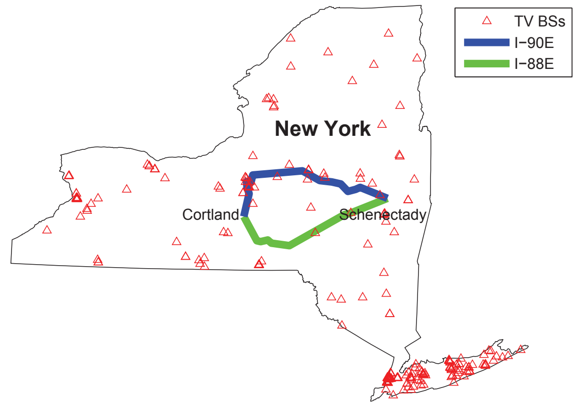

Fig. 12. TV BSs in New York State and route I-88E and I-90E.

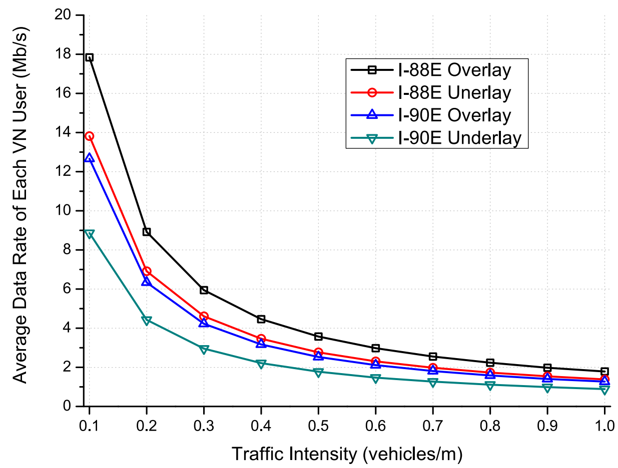

Fig. 13. Average data rate of each VN user on route I-88E and I-90E.

in the Unites States, the spectrum overlay model or the spectrum underlay model? To answer this question, we conduct a case study regarding the current situation of TV BSs in the United States. As shown in Fig. 2, the locations of all TV BSs in the United States are highlighted. Based on these location information, we can estimate the TV BSs' intensity by first calculating and recording the number of TV BSs per 10^3 km^2 which are a series of samples supposed to follow the Poisson distribution, and then estimating the λ according to the distribution in (16) with the maximum likelihood method. The number and intensity of TV BSs in each state of the United States are shown in Fig. 10, where we can see that Utah has the largest number of TV BSs and CA ranks the second. For the intensity, New Jersey ranks the first with $\lambda = 0.01582$, followed by Delaware with $\lambda = 0.01186$. This is also consistent with our observation from Fig. 2, i.e., the northeast areas have densest TV BSs. According to the performance comparison in Fig. 9, we can infer that New Jersey, Delaware and Utah should adopt the spectrum underlay model, while other states should adopt the spectrum overlay model. Overall, the results in Fig. 10 reveal that the TV BSs are still relatively sparse, and the spectrum overlay model is more preferable than the spectrum underlay model for most areas of current United States.

B. Route Selection Evaluation

In this subsection, we evaluate the proposed route selection schemes by investigating a case study on the routes between Cortland and Schenectady in New York State. As shown in Fig. 11, Google map suggests two routes from Cortland to Schenectady, I-88E and I-90E with similar distance and travel time. In Fig. 12, we show the locations of TV BSs in New York State with the highlight of these two routes, from which we can see that the intensity of TV BSs around route I-88E appears to be less than that around route I-90E. By using the similar intensity estimation method in the previous subsection, we can estimate the TV BSs' intensities around route I-88E and I-90E as $\lambda_{88} = 0.00133$ and $\lambda_{90} = 0.00325$, respectively. In such a case, the expected downlink throughput of the vehicular network in those two routes under spectrum overlay and underlay models can be obtained in Table II, where the average distance between the VN user and the nearest VN BS is given as $d_{v,v} = 20$ meters. Based on the downlink throughput calculation, we can plot the instantaneous average data rate that can be obtained by each VN user under different traffic intensities in Fig. 13, where the quantization level is set as $L = 10$ within [0, 1] and the percentage of VN users among all vehicles is considered as $\rho = 0.1$. From the figure, we can see that the network performance in route I-88E is better that that in route I-90E under both spectrum overlay and underlay models due to the less intensity of TV BSs around route I-88E. This is consistent with our analysis that the more TV BSs are located near the route, the less data rate can be obtained by the VN users.

TABLE II
EXPECTED DOWNLINK THROUGHPUT.

	Spectrum overlay	Spectrum underlay
I-88E	$R_{88}^{\text{OL}} = 33.91$ Mb/s	$R_{88}^{\text{UL}} = 26.26$ Mb/s
I-90E	$R_{90}^{\text{OL}} = 24.07$ Mb/s	$R_{90}^{\text{UL}} = 16.84$ Mb/s

TABLE III
INSTANTANEOUS ROUTE SELECTION RESULTS FOR SPECTRUM OVERLAY MODEL.

μ_{88} \ μ_{90}	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	1	1	1	1	1	1	1	1	1	1
0.2	0	1	1	1	1	1	1	1	1	1
0.3	0	0	1	1	1	1	1	1	1	1
0.4	0	0	1	1	1	1	1	1	1	1
0.5	0	0	0	1	1	1	1	1	1	1
0.6	0	0	0	0	1	1	1	1	1	1
0.7	0	0	0	0	1	1	1	1	1	1
0.8	0	0	0	0	0	1	1	1	1	1
0.9	0	0	0	0	0	0	1	1	1	1
1.0	0	0	0	0	0	0	0	1	1	1

We first evaluate the instantaneous route selection scheme, where the VN users make route selection based on the immediate traffic intensity information. In our case study, according to the average data rate per user in Fig. 13, the VN user can easily select the route with higher data rate according to the current traffic intensities of route I-88E and I-90E, i.e., the instantaneous route selection scheme: $\arg\max\{U(\mu_{88}), U(\mu_{90})\}$. We summarize the instantaneous route selection results of both spectrum overlay and underlay models in Table III and Table IV, where "1" means selecting I-88E and "0" means selecting I-90E. For example, when the traffic intensity on route I-88E is $\mu_{88} = 0.1$ vehicle/m (the average distance between two vehicles is 10 m) and that on route I-90E is $\mu_{90} = 0.2$ vehicle/m, the VN user should select I-88E; while when $\mu_{88} = 0.2$ vehicle/m and $\mu_{90} = 0.1$ vehicle/m, the VN user should selecte I-90E. Note that there exists the threshold structure in each row and column of the selection results matrix and the thresholds of the spectrum overlay and underlay models are different. In the practical scenario, those route selection results can be calculated off-line and stored in a table for the VN users. In addition, due to the threshold structure, the VN users only need to store the threshold point on each row or column for the sake of storage saving.

We then evaluate the long-term route selection scheme, where the VN users make route selection based on not only the immediate traffic intensity but also the traffic intensity transitions in the near future. The traffic intensity transition probabilities can be estimated using the 2011 traffic volume dataset provided by the Department of Transportation of New York State [40]. This traffic volume dataset contains both short count data and continuous count data, where the continuous count data comes from equipment built permanently on the road that are intended to operate 365 days a year, while the short count data comes from portable equipment that take counts lasting from 2 days to 7 days. There are five elements in the dataset, the road ID (all roads in New York State are broken into segments and assigned a unique ID), the date and time (the ending time of the record interval in military time), the direction (northbound or eastbound), the lane number (left lane, middle lanes or right lane) and

TABLE IV
INSTANTANEOUS ROUTE SELECTION RESULTS FOR SPECTRUM UNDERLAY MODEL.

μ_{88} \ μ_{90}	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	1	1	1	1	1	1	1	1	1	1
0.2	0	1	1	1	1	1	1	1	1	1
0.3	0	1	1	1	1	1	1	1	1	1
0.4	0	1	1	1	1	1	1	1	1	1
0.5	0	0	1	1	1	1	1	1	1	1
0.6	0	0	0	1	1	1	1	1	1	1
0.7	0	0	0	0	1	1	1	1	1	1
0.8	0	0	0	0	0	1	1	1	1	1
0.9	0	0	0	0	0	1	1	1	1	1
1.0	0	0	0	0	0	0	1	1	1	1

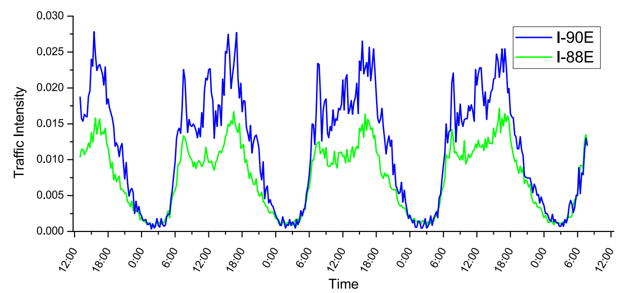

Fig. 14. Traffic intensity of route I-88E and I-90E between Cortland and Schenectady in New York State from 06/20/2011 to 06/24/2011 with sampling interval 15 minutes.

the accumulated number of passing vehicles. The sampling interval in the dataset is typically one hour, while for some location, data is also collected in smaller sampling intervals (15 minute, 10 minute, 5 minute, etc.). An example of the dataset can be seen in Fig. 3 in Section II. Note that the traffic volume c should be converted to the traffic intensity μ. Suppose the sampling interval is $s = 0.25$ hour and the average vehicle speed is $v = 100$ km/h, the traffic intensity can be calculated by $\mu = \frac{c}{1000sv}$. In Fig. 14, we show the estimated traffic intensity of route I-88E and I-90E between Cortland and Schenectady from 06/20/2011 to 06/24/2011 with sampling interval $s = 0.25$ hour. From the figure, we can see that the traffic intensity exhibits the periodical phenomenon for every 24 hours, reaching the peak value at about 18:00 everyday and the valley value at about 3:00 everyday. Moreover, we can also see that the traffic on route I-90E is averagely heavier than that on route I-88E.

According to the traffic intensity data, we can further estimate the traffic intensity transition probabilities $\mathbf{P}$ of route I-88E and I-90E between Cortland and Schenectady, where the quantization level is set as $L = 5$ within [0, 0.03]. To verify the estimation of transition probabilities is accurate, we divide the whole-year dataset regarding route I-88E and I-90E into two halfs, where the first half year is used to train the transitions probabilities and the second half year is used for testing. In Fig. 15, we show the differences between the estimated $\mathbf{P}_e$ (from Jan. to Jun.) and the testing data $\mathbf{P}_t$ of each month (from Jul. to Dec.), i.e., the y-axis is $||\mathbf{P}_e - \mathbf{P}_t||_2$. We can see that the estimated transition probabilities match well with the testing ones, which means that the estimated results can well predict the route intensity transitions in the future. Fig. 16 shows the long-term expected data rate of each VN user under different traffic intensity levels calculated by (15). Similar to the instantaneous scheme, the VN user's data rate performance

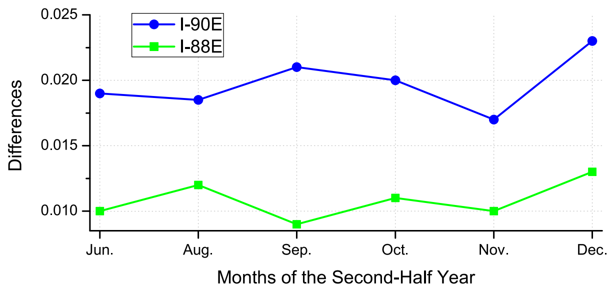

Fig. 15. Accuracy verification of traffic intensity estimation.

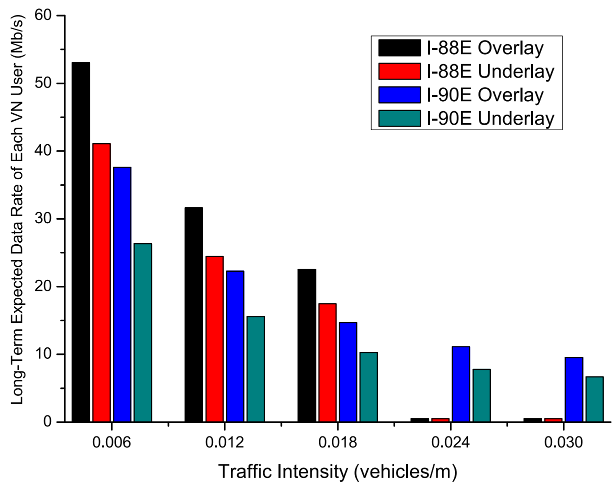

Fig. 16. Long-term expected data rate of each VN user on route I-88E and I-90E.

on route I-88E is better than that on route I-90E due to the lower traffic intensity. Since the maximum traffic intensity on route I-88E is less than 0.024 vehicle/m, there is no physical meaning for the long-term data rate on route I-88E when the traffic intensity level is 0.024 vehicle/m and 0.03 vehicle/m, which are denoted as 0 in Fig. 16. Based on the long-term data rate evaluation, we can further calculate the VN users' long-term route selection results when confronting with different traffic intensities of route I-88E and I-90E, which are listed in Table V for both spectrum overlay and underlay models since the selection restuls of these two models are same with each other in this case. Similar to the instantaneous scheme, there also exists threshold structure in the long-term selection matrix. Since both the intensity of TV BSs around route I-88E and the average traffic intensity of route I-88E are all less than those of route I-90E, we can see that route I-88E is preferable for the VN users in most cases as shown in Table V.

VI. Conclusion

In this paper, we considered the route selection problem in the cognitive vehicular networks from a novel throughput optimization point of view by using TV white space. By considering the TV BSs as PPP distributed, we analyzed the vehicular network throughput under both spectrum overlay and underlay models. The case study on current United States showed that spectrum overlay model is more suitable for most of states, except New Jersey, Delaware and Utah. Based on the vehicular network performance analysis, we further proposed two route selection schemes: instantaneous scheme and long-term scheme. Another case study was conducted regarding the route I-88E and I-90E selection between Cortland and Schenectady in New York State, which showed that I-88E can provide higher average data rate for each individual VN user. In summary, the work in this paper provides a set of comprehensive and effective solutions for analyzing the cognitive vehicular networks from both theoretic and practical perspectives.

TABLE V
Long-Term Route Selection Results for Spectrum Overlay and Underlay Models.

μ_{88} \ μ_{90}	0.006	0.012	0.018	0.024	0.03
0.006	1	1	1	1	1
0.012	0	1	1	1	1
0.018	0	1	1	1	1

References

[1] K. J. R. Liu and B. Wang, *Cognitive Radio Networking and Security: A Game Theoretical View*. Cambridge University Press, 2010.
[2] C. Jiang, Y. Chen, K. J. R. Liu, and Y. Ren, "Renewal-theoretical dynamic spectrum access in cognitive radio networks with unknown primary behavior," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 3, pp. 406–416, 2013.
[3] B. Wang and K. J. R. Liu, "Advances in cognitive radios: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, 2011.
[4] H. Kim and K. G. Shin, "Admission and eviction control of cognitive radio users at wi-fi 2.0 hotspots," *IEEE Trans. Mobile Compt.*, vol. 11, no. 11, pp. 1666–1677, 2012.
[5] O. Younis, L. Kant, A. McAuley, K. Manousakis, D. Shallcross, K. Sinkar, K. Chang, K. Young, C. Graff, and M. Patel, "Cognitive tactical network models," *IEEE Commun. Mag.*, vol. 48, no. 10, pp. 70–77, 2010.
[6] B. Wang and K. J. R. Liu, "Advances in cognitive radios: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, 2011.
[7] M. D. Felice, R. Doost-Mohammady, K. R. Chowdhury, and L. Bononi, "Smart radios for smart vehicles: Cognitive vehicular networks," *IEEE Veh. Technol. Mag.*, vol. 7, no. 2, pp. 26–33, 2012.
[8] P. Papadimitratos, A. Fortelle, K. Evenssen, R. Brignolo, and S. Cosenza, "Vehicular communication systems: Enabling technologies, applications, and future outlook on intelligent transportation," *IEEE Commun. Mag.*, vol. 47, no. 11, pp. 84–95, 2009.
[9] D. Williams, "The arbitron national in-car study," [Online]. Available: http://www.arbitron.com /downloads/InCarStudy2009.pdf.
[10] A. J. Ghandoura, K. Fawaz, H. Artail, M. Felice, and L. Bononi, "Improving vehicular safety message delivery through the implementation of a cognitive vehicular network," *Ad Hoc Networks*, vol. 11, no. 8, p. 2408C2422, 2013.
[11] M. Amadeo, C. Campolo, and A. Molinaro, "Enhancing IEEE 802.11p/WAVE to provide infotainment applications in VANETs," *Ad Hoc Networks*, vol. 10, no. 2, p. 253C269, 2012.
[12] D. Jiang and L. Delgrossi, "Ieee 802.11p: Towards an international standard for wireless access in vehicular environments," in *Proc. IEEE VTC*, 2008-Spring, pp. 2036–2040.
[13] Wikipedia, "Super wi-fi," [Online]. Available: http://en.wikipedia.org/wiki/Super_Wi-Fi.
[14] Google, "Spectrum database," [Online]. Available: https://www.google.com/get/spectrumdatabase/data.
[15] X. Wang and P. Ho, "A novel sensing coordination framework for CR-VANETs," *IEEE Trans. Veh. Technol.*, vol. 59, no. 4, pp. 1936–1948, 2010.
[16] H. Li and D. K. Irick, "Collaborative spectrum sensing in cognitive radio vehicular ad hoc networks: Belief propagation on highway," in *Proc. IEEE VTC*, 2010-Spring, pp. 1–5.
[17] M. Felice, K. R. Chowdhury, and L. Bononi, "Analyzing the potential of cooperative cognitive radio technology on inter-vehicle communication," in *Proc. IFIP Wireless Days (WD)*, 2010, pp. 1–6.
[18] M. Felice, A. J. Ghandour, H. Artail, and L. Bononi, "Integrating spectrum database and cooperative sensing for cognitive vehicular networks," in *Proc. IEEE VTC*, 2013-Fall, pp. 1–7.

[19] H. Kremo and O. Altintas, "On detecting spectrum opportunities for cognitive vehicular networks in the TV white space," *J. Sign. Process. Syst.*, vol. 73, no. 3, p. 243C254, 2013.
[20] K. Tsukamoto, S. Matsuoka, O. Altintas, M. Tsuru, and Y. Oie, "Distributed channel coordination in cognitive wireless vehicle-to-vehicle communications," in *Proc. Int'l Conf on Wireless Access in Vehicular Environments (WAVE)*, 2008, pp. 1–7.
[21] S. Chung, J. Yoo, and C. Kim, "A cognitive MAC for VANET based on the WAVE systems," in *Proc. Int'l Conf on Advanced Communication Technology (ICACT)*, 2009, pp. 41–46.
[22] K. Tsukamoto, Y. Omori, O. Altintas, M. Tsuru, and Y. Oie, "On spatially-aware channel selection in dynamic spectrum access multi-hop inter-vehicle communications," in *Proc. IEEE VTC*, 2009-Fall, pp. 1–7.
[23] D. Niyato, E. Hossain, and P. Wang, "Optimal channel access management with qos support for cognitive vehicular networks," *IEEE Trans. Mobile Comput.*, vol. 10, no. 5, pp. 573–591, 2011.
[24] N. Cheng, N. Zhang, N. Lu, X. Shen, J. W. Mark, and F. Liu, "Opportunistic spectrum access for CR-VANETs: A game theoretic approach," *IEEE Trans. Veh. Technol.*, vol. PP, no. 99, pp. 1–15, 2014.
[25] M. Felice, K. R. Chowdhury, and L. Bononi, "Cooperative spectrum management in cognitive vehicular ad hoc networks," in *Proc. IEEE VNC*, 2010, pp. 1–8.
[26] A. J. Ghandour, K. Fawaz, and H. Artail, "Data delivery guarantees in congested vehicular ad hoc networks using cognitive networks," in *Proc. IEEE IWCMC*, 2011, pp. 871–876.
[27] R. Doost-Mohammady and K. R. Chowdhury, "Design of spectrum database assisted cognitive radio vehicular networks," in *Proc. ICST CROWNCOM*, 2012, pp. 1–5.
[28] K. Fawaz, A. J. Ghandour, M. Olleik, and H. Artail, "Improving reliability of safety applications in vehicle ad hoc networks through the implementation of a cognitive network," in *Proc. IEEE ICT*, 2010, pp. 798–805.
[29] G. P. Villardi, G. T. F. Abreu, and H. Harada, "TV white space technology: Interference in portable cognitive emergency network," *IEEE Trans. Veh. Technol.*, vol. 7, no. 2, pp. 47–53, 2012.
[30] M. Felice, L. Bedogni, and L. Bononi, "Dysco: a dynamic spectrum and contention control framework for enhanced broadcast communication in vehicular networks," in *Proc. ACM MobiWac*, 2012, pp. 97–105.
[31] A. J. Ghandour, K. Fawaz, H. Artail, M. Felice, and L. Bononi, "Improving vehicular safety message delivery through the implementation of a cognitive vehicular network," *Ad Hoc Networks*, vol. 11, no. 8, pp. 2408–2422, 2013.
[32] S. Pagadarail, A. M. Wyglinskil, and R. Vuyyurul, "Characterization of vacant UHF TV channels for vehicular dynamic spectrum access," in *Proc. IEEE VNC*, 2009, pp. 1–8.
[33] O. Altintas, M. Nishibori, T. Oshida, Y. Ihara, M. Saito, C. Yoshimura, Y. Fujii, K. Nishida, K. Tsukamoto, M. Tsuru, and Y. Oie, "Demonstration of vehicle to vehicle communications over TV white space," in *Proc. IEEE VTC*, 2011-Fall, pp. 1–3.
[34] J. Heo, G. Noh, S. Park, S. Lim, E. Kim, and D. Hong, "Mobile tv white space with multi-region based mobility procedure," *IEEE Commun. Lett.*, vol. 1, no. 6, pp. 569–572, 2012.
[35] A. Ameen, E. Mellios, A. Doufexi, N. Dahnoun, and A. Nix, "Lte-advanced downlink throughput evaluation in the 3g and tv white space bands," in *Proc. IEEE PIMRC*, 2013, pp. 771–775.
[36] Y. Yang, L. Shi, and J. Zander, "On the capacity of wi-fi system in tv white space with aggregate interference constraint," in *Proc. IEEE CROWNCOM*, 2013, pp. 123–128.
[37] S. Y. Lee, M. K. Kwon, and S. H. Lee, "Transmit power control scheme for tv white space wireless system," in *Proc. IEEE ICACT*, 2011, pp. 1025–1029.
[38] Y. Guo, C. Guo, C. Feng, D. Li, and X. Li, "Isolation-based uplink power control for td-lte in tv white space," in *Proc. IEEE WPMC*, 2013, pp. 1–5.
[39] Y. Yang, Y. Chen, C. Jiang, C. Wang, and K. J. R. Liu, "Wireless access network selection game with negative network externality," *IEEE Trans. Wireless Commun.*, vol. 12, no. 10, pp. 5048–5060, 2013.
[40] NewYorkState, "Traffic volume data," [Online]. Available: https://www.dot.ny.gov/divisions/engineering/technical-services/highway-data-services/hdsb.
[41] Y. Shi, Y. T. Hou, J. Liu, and S. Kompella, "How to correctly use the protocol interference model for multi-hop wireless networks," in *Proc. ACM MobiHoc*, 2009, pp. 239–248.
[42] M. L. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons, Inc, 1994.
[43] Wikipedia, "North american television frequencies," [Online]. Available: http://en.wikipedia.org/wiki/North_American_tele vision_frequencies.
[44] I. O. D. Cabric, M. Chen, and R. Brodersen, "Spectrum sharing radios," *IEEE Circuits Syst. Mag.*, vol. 6, no. 2, pp. 30–45, 2006.
[45] L. Tian, J. Li, Y. Huang, J. Shi, and J. Zhou, "Seamless dual-link handover scheme in broadband wireless communication systems for high-speed rail," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 4, pp. 708–718, 2012.
[46] H. ElSawy, E. Hossain, and M. Haenggi, "Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 996–1019, 2013.
[47] IEEE, "Part 22.2: Installation and deployment of ieee 802.22 systems," IEEE Computer Society, Tech. Rep., 2012.
[48] FCC, "FM broadcast station classes and service contours," [Online]. Available: http://www.fcc.gov/encyclopedia/fm-broadcast-station-classes-and-service-contours.
[49] J. C. D. Cruz and F. S. Caluyo, "Path loss at the exact location of tv inside residences using digital terrestrial television signal at 677 mhz," *International Journal of Scientific & Technology Research*, vol. 1, no. 6, pp. 24–28, 2012.

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