Information-Sharing Outage-Probability Analysis of Vehicular Networks

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***Abstract*—In vehicular networks, information dissemination/sharing among vehicles is of salient importance. Although diverse mechanisms have been proposed in the existing literature, the related information credibility issues have not been investigated. Against this background, in this paper, we propose a credible information-sharing mechanism capable of ensuring that the vehicles do share genuine road traffic information (RTI). We commence with the outage-probability analysis of information sharing in vehicular networks under both a general scenario and a specific highway scenario. Closed-form expressions are derived for both scenarios, given the specific channel settings. Based on the outage-probability expressions, we formulate the utility of RTI sharing and design an algorithm for promoting the sharing of genuine RTI. To verify our theoretical analysis and the proposed mechanism, we invoke a real-world dataset containing the locations of Beijing taxis to conduct our simulations. Explicitly, our simulation results show that the spatial distribution of the vehicles obeys a Poisson point process, and our proposed credible RTI sharing mechanism is capable of ensuring that all vehicles indeed do share genuine RTI with each other.**

***Index Terms*—Credibility, information dissemination, information sharing, Poisson point process (PPP), reinforcement learning, vehicular networks.**

I. Introduction

VEHICULAR communications and their support networks were originally proposed for public safety applications and traffic efficiency enhancements, which necessitate reliable short-distance vehicle-to-vehicle and vehicle-to-infrastructure communications [1]. With the advent of advanced automobile technology, the globe's population has become more mobile. For example, 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 a staggering 18 h and 31 min [2]. Meanwhile, the vehicular users' demands for in-car communication have also been dramatically increasing, since a wealth of value-added services emerge such as safety message dissemination and in-car entertainment services.

Most of the existing works on information dissemination/sharing were focused on designing specific mechanisms, in particular scenarios of vehicular networks. However, the credibility of the shared road traffic information (RTI) has not been taken into account in those mechanisms. Although all the vehicles act in a cooperative manner, the selfish or malicious ones may share either random or manipulated information for the sake of attaining an unfair road priority. Hence, we consider this problem and propose a mechanism for ensuring that all vehicles share genuine RTI. Furthermore, we define the utility functions of vehicles in the RTI sharing mechanism for the sake of analyzing their incentives in the RTI sharing process, and provide a general analytical framework for the information-sharing outage probability (OP) of vehicular networks. The new contributions of this paper can be summarized as follows.

1) We derive the information-sharing OP of vehicular networks both for the general scenario modeled by Nakagami-m fading and for a more specific highway scenario, where Rayleigh fading is considered.
2) In order to encourage vehicles to share genuine RTI, we design a mechanism based on the reinforcement learning model, where the concept of "reputation" is introduced for circumventing the vehicles' selfish behaviors by exploiting its similarity to human social networks.
3) The real-world dataset containing the locations of Beijing taxis is utilized for verifying the vehicles' spatial distribution characteristics. Based on the parameters inferred with the aid of training from this dataset, we verify our analytical outage performance results as well as the proposed mechanism by our real-world data-driven simulations.

The rest of the paper is organized as follows. We first summarize the related works in Section II. Then, our system model is introduced in Section III. Based on the system model, the information-sharing OP is derived both for the general Nakagami-m as well as for the more specific Rayleigh-distributed highway scenario in Sections IV and V, respectively. In Section VI, we present the proposed RTI sharing scheme, while Section VII provides our real-world data-driven simulation results. Finally, we conclude in Section VIII.

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II. Related Works

The provision of information dissemination/sharing among vehicles is of pivotal significance in vehicular networks, which has been extensively studied in the literature [3]–[21]. Specifically, Zhao *etal.* [3] proposed an architecture and analyzed the dissemination capacity, where the data emanating from the sources were buffered by vehicles and then it was rebroadcast at the intersections. Similarly, the concept of a "smart road" was introduced and an integrated vehicular system was conceived for the collection, management, and provision of context-aware information concerning the traffic density and driver location [4].

Later, the vehicular ad hoc network (VANET) concept was proposed for assisting the dissemination of critical vehicle tracking information [5]. Meanwhile, Cenerario *et. al.* designed an event-related information exchange/sharing protocol relying on a VANET in [6]. With the goal of supporting a wide range of vehicular networks, Ros *et al.* [7] proposed a broadcast algorithm relying on periodic beacon messages, which contained acknowledgments of the circulated broadcast messages. The urban scenario of vehicular networks was studied based on the road map information as prior knowledge in [8] and relying on peer-to-peer (P2P) cooperative caching in [9]. The heterogeneity of radio propagation was taken into account in [10], where the tradeoffs amongst parameters, such as the cost, delay, and optimized system utility, were analyzed. The performance analysis of information sharing in vehicular networks was carried out in [11]–[15]. More specifically, the distribution of concurrent transmissions was analyzed in [11], while the analysis of packet loss rate and packet transmission distance was provided in [12]. The analysis of end-to-end reliability was disseminated in [13], while the throughput and delay analysis was the subject of [14] and [15].

On the other hand, the security issues of vehicular information dissemination were investigated in [16]–[18]. Explicitly, a graph-based metric was proposed for insider attacker detection in [16], whilst a trustworthiness verification model was advocated in [17] and a cooperative neighbor position verification model was conceived in [18]. Moreover, the information sharing in vehicular networks was modeled by carefully adapting the perspective of social networks [19]–[21]. Most of the aforementioned contributions were focused on designing specific mechanisms for information dissemination/sharing in particular scenarios of vehicular networks. However, the credibility of the shared RTI has not been taken into account in those mechanisms, which hence inspired this paper.

III. System Model

As illustrated in Fig. 1, we consider a cooperative vehicular network constituted by a group of vehicles denoted by $\mathcal{S} = \{v_0, v_1, v_2, \ldots, v_i, \ldots\}$. Since all the vehicles are independent of each other, although their locations are geographically constrained by the mesh of roads in a city, they can be viewed as being randomly distributed. By exploiting this property, we assume that the locations of the vehicles obey a Poisson point process (PPP) on the 2-D road mesh with an intensity of λ (the number of vehicles per square kilometer). The PPP has been widely adopted for modeling the distribution of random placements, such as the locations of macrocell and femtocell base stations [22], [23], as well as of ad hoc nodes [24]. In contrast to the existing PPP model of an infinite 2-D plane, the PPP model of a vehicular network is constrained by the road-width, which may nonetheless be as wide as say 100 m in metropolitan areas. Let us denote the road-width by W, which is assumed to be a constant. Based on the PPP model, the number of vehicles in any finite rectangle having a width of W and a length of D is Poisson distributed with a mean of λA_r, which can be expressed as

$$P(N_r = n) = \frac{e^{-\lambda W D} (\lambda W D)^n}{n!}. \tag{1}$$

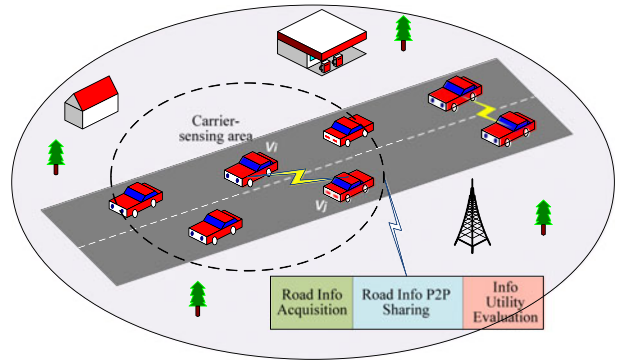

Fig. 1. System model.

In our model, all the vehicles are assumed to be selfish, aiming for maximizing their own utility. We also assume that each vehicle has the capability of acquiring RTI and that they are willing to share it with each other in order to make better-informed decisions. The RTI can be for example the location information invoked for cooperative vehicle localization [25], or the traffic information invoked for cooperative route planning [26]. Our proposed model is general, and hence, it is independent of the specific form of the RTI. As shown in Fig. 1, at the beginning of each time slot, all the vehicles acquire the current RTI by their in-car sensors or by exploiting the driver's judgment. Then, each vehicle has to decide, whether it will truthfully share this information with others or whether to manipulate the shared RTI to render it useless, either, for example, due to privacy concerns or with the objective of gaining an unfair road priority. Therefore, although all the vehicles act in a cooperative manner, they occasionally may share random or manipulated information for the sake of improving their own utility. Then, each vehicle exchanges either its perceived genuine information or the false RTI with the nearest vehicle in a P2P mode. Following the information-sharing phase, each vehicle exploits its own information, as well as the shared information to make an informed decision as to whether to change speed, lanes, routes, or just maintain the current status. Finally, at the end of each time slot, the vehicle evaluates the performance attained as a result of its decision and then adjusts its actions in preparation for the next round. Here, we consider a practical scenario, where a vehicle is unable to ascertain the credibility of the RTI gleaned, until the information is actually utilized for its decision making and until the resultant performance is evaluated. Note that the time slot mentioned in this paper represents a coarse scale, on the order of seconds or minutes. Such a coarse synchronization can be readily achieved by the GPS, which has been widely deployed in vehicles. When it comes to information sharing between two vehicles, a fine-grained physical layer synchronization should be guaranteed for successful data transmission. However, such a fine-grained synchronization is not required for the entire network.

The above-mentioned P2P mode is assumed to be supported by the IEEE 802.11p protocol (a.k.a., the Wireless Access in the Vehicular Environment (WAVE)) relying on the classic Request To Send/Clear To Send (RTS/CTS) mechanism for the sake of avoiding the hidden terminal problem [27][28]. In this case, as shown in Fig. 1, only a single pair of vehicles is sharing information in a time slot within their carrier-sensing range, such as v_i and v_j. Based on this characteristic, the two-directional outage analysis is not considered in this paper, since only a single pair of vehicles is engaged in communication within the range. Nevertheless, the vehicles beyond v_i and v_j's carrier-sensing area may also impose interference on their communications according to the practical interference model of [29]. According to the experimental results of [30], the 5.9 GHz dedicated short-range communications frequency band may be modeled by a Nakagami-*m* fading channel, provided that the distance between two vehicles is below 40 m. By contrast, it is modeled by a Rayleigh-fading channel when it is above 40 m, which is a special case of the Nakagami-*m* fading associated with $m = 1$. A line-of-sight (LOS) Rician channel may also occur under certain circumstances. Nevertheless, we would like to concentrate on the Nakagami-*m* and Rayleigh-fading scenarios, especially when it comes to the metropolitan areas, where the presence of buildings and of the infrastructure may block the LOS as in Beijing city. Thus, the power received by the vehicle v_i from its peer v_j located at a distance of $d_{i,j}$ can be expressed as

$$y_{i,j} = |h_{i,j}|^2 d_{i,j}^{-\alpha_{i,j}} \tag{2}$$

where $\alpha_{i,j}$ is the channel's path loss coefficient and $h_{i,j}$ is the channel gain. Since the distance between a pair of communicating vehicles can be 40 m or higher, $h_{i,j}$ should obey the Nakagami-*m* distribution of [31]:

$$f_{h_{i,j}}(x) = 2\left(\frac{m}{\mu_{i,j}}\right)^m \frac{x^{2m-1}}{\Gamma(m)} \exp\left(-m\frac{x^2}{\mu_{i,j}}\right) \tag{3}$$

where $\Gamma(\cdot)$ is the gamma function, $\mu_{i,j} = \mathbb{E}(|h_{i,j}|^2)$ is the average received power, and m is the Nakagami-*m* fading parameter. In this paper, we only consider integer m values for the sake of mathematical tractability. Let us introduce $g_{i,j} = |h_{i,j}|^2$, where $g_{i,j}$ obeys the gamma distribution of

$$f_{g_{i,j}}(x) = \left(\frac{m}{\mu_{i,j}}\right)^m \frac{x^{m-1}}{\Gamma(m)} \exp\left(-m\frac{x}{\mu_{i,j}}\right). \tag{4}$$

When using the IEEE 802.11p protocol, all the vehicles that impose interference on the vehicle v_i in Fig. 1 should be located farther than 40 m [30]. In this case, the Rayleigh-fading model should be considered for the link imposing interference by the vehicle v_k upon v_i, i.e., $g_{i,k}$ should obey the exponential distribution of

$$f_{g_{i,k}}(x) = \frac{1}{\mu_{i,k}} \exp\left(-\frac{x}{\mu_{i,k}}\right). \tag{5}$$

IV. Channel-Induced Outage Probability in a General Scenario

In this section, we theoretically analyze the channel-induced OP of vehicular networks. The classic channel-induced OP of a specific vehicle v_i is defined as the probability of v_i's signal-to-interference-plus-noise ratio (SINR) dipping below a threshold of Υ, i.e.,

$$p_{v_i} = \mathbb{P}[\gamma_{v_i} \leq \Upsilon] \tag{6}$$

which, in fact, is also the cumulative distribution function (c.d.f) of this vehicle's SINR. Since the channel-induced OP is a physical-layer metric, the fact of whether a vehicle shares genuine or false information is irrelevant in this section. By contrast, in Section V, we will use the channel-induced OP for modeling the vehicles' future utility trend, depending on whether they are sharing genuine or false RTI.

As illustrated in the system model, we consider a P2P scenario, where every pair of closest vehicles exchange their respective RTI within each time slot. For a specific vehicle v_0, its closest counterpart v_1 should be the intended information-sharing peer. Let us denote the distance and channel gain of v_0 with respect to the transmitter of the vehicle v_1 by d_1 and g_1, respectively. Then, the SINR of the vehicle v_0 can be written as

$$\gamma_0 = \frac{g_1 d_1^{-\alpha_1}}{\Lambda} \tag{7}$$

where α_1 is the path loss coefficient, and Λ is the interference imposed by the other vehicles on the vehicle v_0 plus the noise power. Let us assume that v_1 is the vehicle closest to v_0. Then, according to the experimental results of [30], the channel gain g_1 should obey the gamma distribution as in (4) with a mean of $\mathbb{E}[g_1] = \mu_1$ and Nakagami-*m* fading parameter of m_1. During the information sharing between the pair of vehicles v_0 and v_1, the signals of all other vehicles, represented by v_i $(\forall v_i \in \mathcal{S}\backslash\{v_0, v_1\})$, should be considered as interference. Let us denote the distance and channel gain between v_i and v_0 by d_i and g_i, respectively. In this case, the interference plus noise power Λ can be calculated by

$$\Lambda = \sum_{v_i \in \mathcal{S}\backslash\{v_0, v_1\}} g_i d_i^{-\alpha_2} + \sigma^2 \tag{8}$$

where α_2 is the path loss coefficient and σ^2 is the variance of the zero-mean circularly symmetric complex-valued Gaussian noise. Assuming that the other vehicles—except for the closest one—are relatively far from v_0, Rayleigh fading prevails between v_i and v_0, i.e., the interfering channel's gain g_i obeys the exponential distribution as in (5). Since all vehicles are independent of each other, the channel gains $\{g_{i, v_i \in \mathcal{S}\backslash\{v_0, v_1\}}\}$ are independent identically distributed (i.i.d.), where $\mathbb{E}[g_{i, v_i \in \mathcal{S}\backslash\{v_0, v_1\}}] = \mu_2$. Thus, the SINR of vehicle v_0 becomes

$$\gamma_0 = \frac{g_1 d_1^{-\alpha_1}}{\sum_{v_i \in \mathcal{S} \setminus \{v_0, v_1\}} g_i d_i^{-\alpha_2} + \sigma^2} \tag{9}$$

while the channel-induced OP of vehicle v_0 in sharing information with v_1 is formulated as

$$p_0 = \mathbb{E}_{g_1, d_1, g_i, d_i}\left[\mathbb{P}(\gamma_0 \le \Upsilon)\right]. \tag{10}$$

In the following theorem, the channel-induced OP expression of vehicle v_0 is formulated for a specific time slot.

Theorem 1: In a vehicular network relying on the 802.11p protocol and RTS/CTS, a vehicle's information-sharing OP can be expressed as

$$p_0 = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \sum_{k=0}^{m_1-1} \frac{(-m_1 \tau^{\alpha_2} \Upsilon)^k}{k! \mu_1^k} \left.\frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k}\right|_{s=\frac{m_1 \tau^{\alpha_1} \Upsilon}{\mu_1}} e^{-2\lambda W \tau} \mathrm{d}\tau \tag{11}$$

where the target SINR is Υ and we have

$$\Phi_\alpha(x) = x^{1/\alpha} \int_{x^{-1/\alpha}}^{+\infty} \frac{1}{1+u^\alpha} \mathrm{d}u. \tag{12}$$

Proof: See the proof in Appendix A.

V. Information-Sharing Outage Performance in Highway Scenario

In *Theorem 1*, (11) provides the information-sharing OP of vehicular networks in a general form, which can be used in any arbitrary scenario, including both dense and sparse vehicular network scenarios. However, when considering specific application scenarios, further approximations can be adopted in the derivation of *Theorem 1*. In this section, we will consider a highway-specific scenario, where the distance amongst vehicles may be substantially higher than in the downtown area, say over 30 m on average. According to the experimental results of [30], the channel between a pair of vehicles in this highway scenario is Rayleigh fading, which implies that the channel between vehicle v_1 and v_0 is Rayleigh fading. Hence, g_1 in (7) obeys follow the exponential distribution with the same mean as g_i. In essence, this specific Rayleigh-fading highway scenario constitutes a special case of Nakagami-*m* fading associated with $m = 1$. The following corollary formulates the channel-induced OP in this highway scenario.

Corollary 1: In a highway vehicular network relying on the 802.11p protocol and RTS/CTS, a vehicle's information-sharing OP can be expressed as

$$p_0^{\mathrm{hwy}_1} = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu} \tau^{\alpha_1}\right) \cdot \exp\left[-2\lambda W \Upsilon^{\frac{1}{\alpha_2}} \tau^{\frac{\alpha_1}{\alpha_2}} \mathcal{G}_{\alpha_2}\left(\left(\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon}\right)^{\frac{1}{\alpha_2}}\right)\right] \cdot e^{-2\lambda W \tau} \mathrm{d}\tau \tag{13}$$

where we have

$$\mathcal{G}_\alpha(x) = \int_x^{+\infty} \frac{1}{1+u^{\alpha/2}} \mathrm{d}u. \tag{14}$$

Proof: See the proof in Appendix B.

According to the experimental results of [30], in the highway scenario the path loss measurements showed a dual-slope model, having a break-point at the distance of 100 m. When the distance between two vehicles is below 100 m, the path loss coefficient is α, while beyond 100 m it is β. Since 100 m is already at the limit of the 802.11p-based P2P information sharing, we can focus our attention on considering the scenario, where all vehicles' path loss models are identical, i.e., $\alpha_1 = \alpha_2 = \alpha$. Specifically, the experimental results of [30] showed that the path loss coefficient is $\alpha = 2$ under 100 m. The channel-induced OP of this specific scenario is formulated in the following corollary.

Corollary 2: In a highway vehicular network using the 802.11p protocol and RTS/CTS, where the path loss coefficients amongst the vehicles are identical, a vehicle's information-sharing OP can be expressed as

$$p_0^{\mathrm{hwy}_2} = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \times \left[-\frac{\sigma^2 \Upsilon}{\mu} \tau^\alpha - 2\lambda W \Big(1 + \Phi_\alpha(\Upsilon)\Big) \tau\right] \mathrm{d}\tau. \tag{15}$$

Specifically, when the channel's path loss coefficient is $\alpha = 2$, the closed-form expression of the channel-induced OP can be formulated as

$$p_0^{\mathrm{hwy}_2} = 1 - 2\lambda W \sqrt{\frac{\pi}{\chi_1(\Upsilon)}} \exp\left(\frac{\chi_2^2(\Upsilon)}{4\chi_1(\Upsilon)}\right) \times Q\left(\frac{\chi_2(\Upsilon)}{\sqrt{2\chi_1(\Upsilon)}}\right) \tag{16}$$

where $\chi_1(\Upsilon)$ and $\chi_2(\Upsilon)$ are

$$\chi_1(\Upsilon) = \frac{\sigma^2}{\mu} \Upsilon \tag{17}$$

$$\chi_2(\Upsilon) = 2\lambda W \left(1 + \sqrt{\Upsilon} \arctan \sqrt{\Upsilon}\right). \tag{18}$$

Proof: See the proof in Appendix C.

It can be seen that (16) gives a simple closed-form expression for a single vehicle's information-sharing OP, which simply relies on the calculation of the Q-function. If we now consider the specific scenario, where the channel noise is negligible compared to the interference arriving from the other vehicles v_i, i.e., for $\sigma^2/\Lambda \to 0$, the information-sharing OP can be further simplified using the following corollary.

Corollary 3: In a highway vehicular network associated with the 802.11p protocol and RTS/CTS, where the path loss coefficients of all vehicles are identical and the channel noise is negligible compared to the interference, a vehicle's information-sharing OP during a specific time slot can be expressed as

$$p_0^{\mathrm{hwy}_3} = \frac{\Phi_\alpha(\Upsilon)}{1 + \Phi_\alpha(\Upsilon)}. \tag{19}$$

Specifically, when the channel's path loss coefficient is $\alpha = 2$, we have

$$p_0^{\mathrm{hwy}_3} = \frac{\sqrt{\Upsilon} \arctan \sqrt{\Upsilon}}{1 + \sqrt{\Upsilon} \arctan \sqrt{\Upsilon}}. \tag{20}$$

Proof: Equations (19) and (20) can be readily obtained by setting $\sigma^2 = 0$ in (15) and (16), respectively.

By now, we have completed the theoretical information-sharing OP analysis, which is an important metric that reflects whether information sharing can be reliably accomplished. Note that successful information sharing in the vehicular network relies both on successful transmission in the presence of no channel-induced outage and no genuine-information-sharing outage. Based on the channel-induced OP analysis of this section, the next section will propose a RTI sharing mechanism that ensures for the vehicles to share genuine information.

VI. Road Traffic Engineering Sharing Mechanism

In the previous section, we have studied the information-sharing OP of the vehicular network considered. Following the above performance analysis, this section will consider the vehicles' information-sharing strategies, utilities, and interactions during the RTI sharing process. Note that the sharing of RTI cannot succeed if a channel-induced outage happens between the vehicles. Let us consider a cooperative vehicular network supporting N selfish vehicles indexed as $\{v_1, v_2, ..., v_N\}$, each aiming for maximizing its own utility. As mentioned in the introduction, although all vehicles share the RTI in a cooperative manner, their specific degree of altruism/selfishness determines whether they may share false or genuine RTI for the sake of improving their own utility by exploiting unfair priority on the road for example. Considering this issue, each vehicle v_i is assumed to have a binary action space defined as follows:

$$a_i = \begin{cases} \mathbf{S}_G: & \text{sharing genuine RTI} \\ \mathbf{S}_F: & \text{sharing false RTI.} \end{cases} \tag{21}$$

As a counterpart, a mixed strategy can also be defined for vehicle v_i in which q_i represents the probability of vehicle v_i sharing genuine RTI, complemented by a $(1 - q_i)$ probability of false RTI. As mentioned in the system model, each vehicle evaluates the RTI gleaned from its peer vehicle at the end of each time slot. Additionally, we also consider a binary information reward space, where the genuine RTI earns a reward of R, while the issuance of false RTI results in a zero reward. In such a case, we can summarize vehicle v_i's utility functions as follows:

$$\begin{cases} U_{\mathrm{ij}}(\mathbf{S}_G, \mathbf{S}_G) = (1 - p_{\mathrm{ij}})R - c_i \\ U_{\mathrm{ij}}(\mathbf{S}_G, \mathbf{S}_F) = -c_i \\ U_{\mathrm{ij}}(\mathbf{S}_F, \mathbf{S}_G) = (1 - p_{\mathrm{ij}})R \\ U_{\mathrm{ij}}(\mathbf{S}_F, \mathbf{S}_F) = 0 \end{cases} \tag{22}$$

where $U_{\mathrm{ij}}(a, b)$ represents vehicle v_i's utility, when its strategy is a and its peer v_j's strategy is b with p_{ij} denoting the channel-induced OP between v_j and v_i, and $c_i > 0$ represents the additional cost of sharing genuine information. Then, $(1 - p_{\mathrm{ij}})R$ quantifies the expected reward. Additionally, it is assumed that the link's OP p_{ij} should be no higher than $1 - \frac{c_i}{R}$; otherwise, no vehicle would share genuine RTI under any circumstances.

The credit mechanism of the vehicular networks considered may be designed by observing human social networks. The concept of "reputation" is rather important for everyone in the real world, where a person's credit/reputation is generated and updated according to his/her accumulated behaviors in human social networks. Explicitly, when interacting with a reputable person, we are inclined to maintain future contacts with him/her. On the other hand, if we learned a lesson from interacting with someone having a bad reputation, a long-lasting cooperation may be unlikely. Similarly, in our cooperative vehicular network, each vehicle can evaluate the others' credit through learning from its interactions with other vehicles. In this case, a vehicle can determine whether to share its RTI with a specific vehicle according to that vehicle's credit/reputation. When a vehicle's credit is below a certain threshold, other vehicles would not share any RTI with it. It is expected that through rounds of interactions, each vehicle's credit can be gradually learned by the observations and evaluations of its shared RTI. According to this credit information, the vehicles associated with a low credit would obtain less and less shared RTI, and eventually they will have to change their RTI sharing strategy to improve their reputation. We assume that there is a central server and each vehicle can report its experience in sharing RTI with all others. As a result, the database records the vehicles' credit. The credit established by each vehicle is considered to be private information, which may not be appropriate for the server to release to the public. This is similar to our human social network, where the credit earned by each individual is not directly visible to others. Nevertheless, through rounds of interactions, one vehicle's credit can be gradually learned by others. Note that the central server is only used by the vehicles to inform the others about their RTI sharing experience and to store the credit value of each vehicle. Since the experience can be quantized to a low number of discrete levels, the amount of data related to each vehicle is relatively small. Therefore, the server does not have to maintain a large-scale database. A potential solution is that each vehicle stores its own experience and the credit values of other vehicles locally.

Similar to the human social networks, each vehicle of our vehicular network can have a credit value generated by its past behavior, and also determines its future behavior when sharing RTI with others. Let us define vehicle v_i' reputation value as r_i in conjunction with $0 \le r_i \le 1$. Note that in human social networks, a person's behavior is typically consistent with his/her reputation, regardless of the specific credit of the other persons he/she is interacting with. Similarly, vehicle v_i's RTI sharing strategy q_i should also be consistent with its reputation r_i, and thus these two parameters can be deemed to be identical, i.e., we have $r_i = q_i$. When v_i has the knowledge of vehicle v_j's credit/reputation through rounds of RTI sharing interactions, v_i can determine whether to cooperate with v_j in the future. Let us define v_i's interaction probability and action with respect to other vehicles as

$$\boldsymbol{\kappa}_i = [\kappa_{i1}, \kappa_{i2}, \ldots, \kappa_{\mathrm{iN}}] \tag{23}$$

$$\boldsymbol{\eta}_i = [\eta_{i1}, \eta_{i2}, \ldots, \eta_{\mathrm{iN}}] \tag{24}$$

where $0 \le \kappa_{\mathrm{ij}} \le 1$ represents v_i's probability of sharing RTI with v_j, regardless whether this is genuine or false information, and $\eta_{\mathrm{ij}} = 0$ or 1 represents whether or not to cooperate with v_j in a specific time slot. In such a scenario, at the beginning of each time slot, each vehicle first has to determine its next action η_{ij}, i.e., whether to cooperate with the nearest vehicle v_j, according to v_i's interaction probability κ_{ij}. Then, if it has decided to share RTI with v_j, it has to further determine the RTI sharing action a_i, i.e., as to whether to share genuine or false RTI with a specific peer vehicle, according to both v_i's information-sharing strategy q_i as well as to its reputation r_i.

Meanwhile, after rounds of RTI sharing interactions, vehicle v_i should update its interaction probability $\boldsymbol{\kappa}_i$ according to its experience with the others or by querying the database. It is expected that through a series of alternating decision making and learning processes, the vehicles having a bad reputation would obtain decreasingly less shared RTI from the others, and thus they would have to ameliorate their credit/reputation by actively sharing genuine RTI hereafter.

During the multiround RTI sharing process, none of the vehicles has access to the other vehicles' information-sharing strategies, actions, and utilities. Moreover, due to the rapidly evolving topology of vehicular networks, each vehicle may share its RTI with different vehicles during different time slots. Hence, from an individual vehicle's perspective, the network including all other vehicles can be regarded as an external environment, within which the vehicle makes decisions and shares RTI with the goal of maximizing its own utility. Generally, each vehicle learns from its interactions with this dynamic environment and adapts to the environment by adjusting its strategies for the sake of gleaning an increased utility. Reinforcement learning is a powerful tool capable of solving such an adaptive environment-learning and decision-making problem [32]. Its actions are reminiscent of how an intelligent agent infers the unknown statistical features of its environment as well as its actions in the environment so as to maximize a certain notion of the cumulative reward, where the environment itself is gradually changed by the agent's actions. Reinforcement learning has been widely adopted in communications and networks [33], [34], control [35], finance, and economics [36], as well as in social science [37], [38].

In our model, one of the main technical problems is how each vehicle constructs its interaction probability vector $\boldsymbol{\kappa}_i$ after rounds of RTI sharing interactions with the others. Based on the reinforcement learning model, each vehicle should first construct its perception through learning the others' inclination in RTI sharing. The *perception* is a quantitative representation of the accumulated utilities, which records all the historical interactions of the past as well as the new interaction results. In other words, it relies on the exploitation of past knowledge and on the exploration of a new environment [32]. Let us define vehicle v_i's perception of the others' behaviors as $\mathbf{z}_i$, where

$$\mathbf{z}_i = [z_{i1}, z_{i2}, \ldots, z_{i\mathrm{N}}] \tag{25}$$

with z_{ij} being vehicle v_i's perception with respect to v_j. At the end of each time slot, v_i first evaluates the utility of information received from v_j and then utilizes this utility value for adjusting its perception associated with v_j, while keeping the perception of others unchanged, which can be expressed as

$$z_{\mathrm{ij}}^{t+1} = \begin{cases} (1-\epsilon_i^t) z_{\mathrm{ij}}^t + \epsilon_i^t U_{\mathrm{ij}}^t, & \text{if } \eta_{\mathrm{ij}}^t = 1 \\ z_{\mathrm{ij}}^t, & \text{if } \eta_{\mathrm{ij}}^t = 0 \end{cases} \tag{26}$$

where the superscript t represents the time slot, U_{ij}^t is v_i's utility gleaned through exchanging information with v_j during time slot t, and ϵ_i^t is a sequence of averaging factors controlling the rate of decay in conjunction with $\sum_t \epsilon_i^t = \infty$ and $\sum_t (\epsilon_i^t)^2 < \infty$. The constraint of $\sum_t \epsilon^t = \infty$ is imposed for ensuring $\epsilon^t > 0$, i.e., the new learned utility U_{ij}^t should always be incorporated. By contrast, the constraint of $\sum_t (\epsilon^t)^2 < \infty$ is used for ensuring $\epsilon^t < 1$, i.e., the history of the learned experience z_{ij}^t should always be utilized.

After updating the perception $\mathbf{z}_i$, vehicle v_i can utilize it for generating its interaction probability with respect to vehicle v_j. Apparently, the more utility v_i can obtain through sharing RTI with vehicle v_j, the higher the interaction probability κ_{ij} should be, which represents a proportional relationship between κ_{ij} and z_{ij}. Here, we adopt a normalized performance evaluation method based on the *Boltzmann* exploration rule formulated as follows [32]:

$$\kappa_{\mathrm{ij}}^t = \frac{e^{\xi_i^t z_{\mathrm{ij}}^t}}{\max\{e^{\xi_i^t z_{\mathrm{ij}}^t}, \forall j\}} \tag{27}$$

where the positive coefficient ξ_j^t controls the exploration level with $\xi_j^t \to 0$ leading to a 0.5 interaction probability, while for $\xi_j^t \to \infty$ the action would concentrate only on one of the pure unconditional cooperation or no cooperation strategy, whichever results in a higher perception. The physical meaning of (27) is that vehicle v_i always shares RTI with that specific vehicle, which can give v_i the highest utility. Then, v_i considers this highest utility as a reference, when it determines its interaction probability with others.

To summarize, the reinforcement learning-based credible RTI sharing scheme can be interpreted as a process, in which each vehicle learns about its utilities as well as perceptions, and then updates its estimation regarding the other vehicles' reputation as well as adjusts its interaction behavior accordingly using its accumulated perception. The evolution from z_{ij}^t to z_{ij}^{t+1} can be illustrated by a chain of iterative elementary steps: the initial perception gives rise to a random interaction probability that determines the interaction; by following the interaction and the information-sharing action, the resultant utility is evaluated and then the perception can be updated in the next round, and so on. The iterations can be simply expressed by the following illustrative chain:

$$\begin{array}{ccccccccc} z_{\mathrm{ij}}^t & \to & \kappa_{\mathrm{ij}}^t & \to & \eta_{\mathrm{ij}}^t & \to & U_{\mathrm{ij}}^t & \to & z_{\mathrm{ij}}^{t+1} \\ & & \downarrow & & & & \uparrow & & \\ & & r_i^t & \to & q_i^t & \to & a_i^t & & \end{array} \tag{28}$$

where the arrow between κ_{ij}^t and r_i^t means that when a vehicle discovers that the number of other vehicles sharing RTI with it is less than a certain threshold, the vehicle would consider to increase its credit value in order to enhance its reputation by

Algorithm 1: Credit mechanism for RTI sharing.

for each vehicle v_i **do**
  /********** *Initialization* **********/
  Initialize v_i's credit value r_i^0 and credit adjustment step size Δr_i.
  Initialize v_i's perception $\mathbf{z}_i^0 = \mathbf{0}$.
  Initialize v_i's interaction probability $\boldsymbol{\kappa}_i^0 = \mathbf{1}$.
  Initialize the number of v_i's cooperative vehicles $n_i^0 = 0$ and the threshold n_{th}.
  Setup the learning speed ϵ_i, the exploration level ξ_i and the tolerance ζ.
  /********** *RTI sharing interaction* **********/
  for each time slot t **do**
    Discover the nearest vehicle v_j.
    Determine η_{ij}^t using random number generator $\mathbf{rand}(\kappa_{\text{ij}}^t)$.
    /********** *Perception adjustment* **********/
    if $\eta_{\text{ij}}^t == 1$ **then**
      Set $s_i^t = r_i^t$ and the RTI sharing action a_i^t using $\mathbf{rand}(q_i^t)$.
      RTI sharing, evaluate the information utility U_{ij}^t.
      Update v_i's perception z_{ij}^t and store n_i^t.
    end if
    /********** *Interaction probability adjustment* **********/
    if $\left(z_{\text{ij}}^t - z_{\text{ij}}^{(t-1)}\right)^2 \geq \zeta$ **then**
      Updatev_i's interaction probability $\kappa_{\text{ij}}^t = e^{\xi_i^t z_{\text{ij}}^t} / \max\{e^{\xi_i^t z_{\text{ij}}^t}, \forall j\}$.
    end if
    /********** *Reputation adjustment* **********/
    if $\frac{1}{t}\sum_t n_i^t < n_{\text{th}}$ **then**
      $r_i = r_i + \Delta r_i$.
    end if
    $t = t + 1$.
  end for
end for

sharing more genuine RTI with the others. The credit mechanism is summarized in Algorithm 1. In the initialization phase, each vehicle may have different prior credit vales and credit adjustment preference. Meanwhile, the learning speed ϵ determines the weight of new information, the exploration level ξ determines the probability of adopting uncharted strategies, while the tolerance determines the learning performance. In the RTI sharing phase, each vehicle first connects with the nearest vehicle and generates the interaction strategy, i.e., whether to interact with the vehicle. If the interaction indicator is positive, the vehicle then shares the genuine RTI with a probability generated by its reputation. Following the information-sharing interaction, the vehicle evaluates its perception and updates the interaction probability in the next round. If the vehicle finds that the number of other vehicles who would like to exchange information with it is below some threshold, the vehicle would

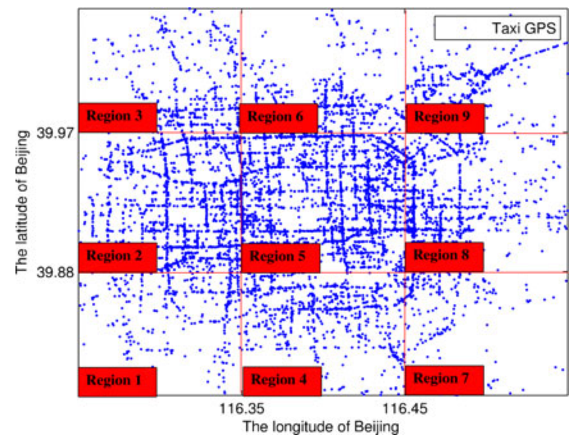

Fig. 2. Locations of Beijing taxis.

TABLE I
VEHICLE INTENSITIES OF DIFFERENT REGIONS AT BEIJING

Region	0	1	2	3	4
Intensity (/km^2)	59.6	23.3	72.7	40.7	48.1
Average distance (m)	89.03	227.79	73.01	130.41	110.42
K-S test (*P*-value)	0.0731	0.1179	0.1061	0.0705	0.0619
Region	5	6	7	8	9
Intensity (/km^2)	76.8	46.3	21.2	74.4	59.6
Average distance (m)	69.12	114.57	250.00	71.35	89.05
K-S test (*P*-value)	0.1169	0.0774	0.0831	0.0584	0.0937

TABLE II
NUMERICAL PARAMETERS FOR PERFORMANCE EVALUATION

Parameter	Value
Max Tx Power	20 dBm
Antennas	1 Tx, 1 Rx
Antennas gains	5 dBm
Nakagami-*m* fading parameter	$m = 2$
Path loss exponent	$\alpha = 2, 4$
Noise power	$\sigma^2 = 0.1$ dBm
Maximum OP	$\Upsilon = 0.1$

adjust its reputation according to the preferred adjustment step size. In the next section, we will conduct simulations to quantify the performance of the proposed algorithm.

VII. SIMULATION RESULTS BASED ON REAL TRAFFIC DATA

In this section, we conduct simulations to verify our theoretical analysis and characterize the proposed schemes. The simulations are based on a real-world dataset consisting of the spatial distribution of Beijing taxis. In the following, we will first estimate the intensity of the taxis in Beijing using the dataset. Then, based on the estimated intensity, we will characterize the outage performance of RTI sharing as well as verify the merits of the proposed RTI sharing scheme.

The real-world dataset contains the GPS positions of 10 258 taxis in Beijing (longitude from 116.25 to 116.55 and latitude from 39.8 to 40.05) during the period of February 2–8, 2008 [39]. As shown in Fig. 2, the positions of these vehicles at a

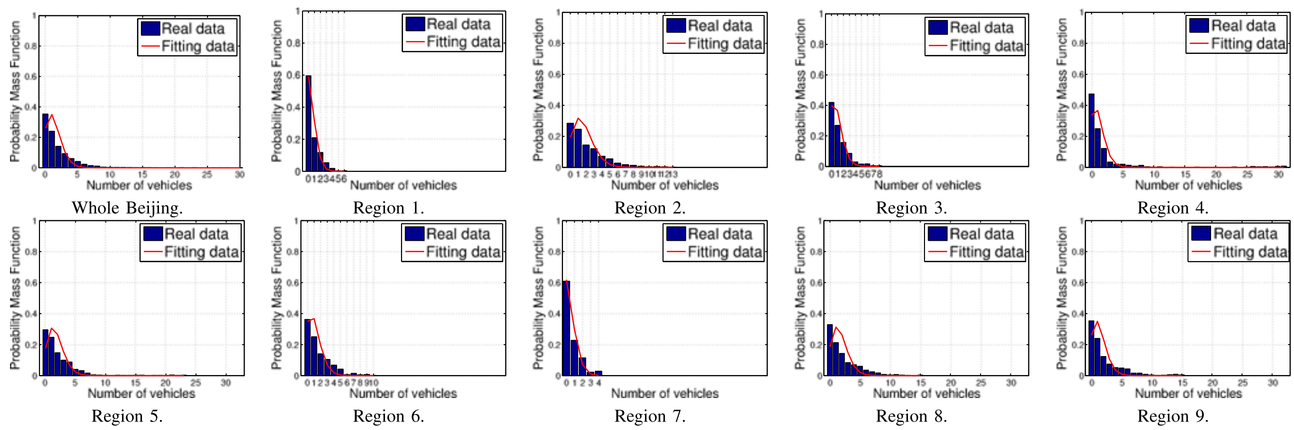

Fig. 3. Taxis position distributions of different regions at Beijing.

specific time instant are illustrated. We can see that the vehicles' position distribution reflects the planning structure of Beijing. Furthermore, we can distinguish the downtown and suburban areas. For the sake of illustrating the specific regional characteristics, instead of painting a picture of the whole city, we separate Beijing city into nine regions, as shown in Fig. 2. Based on the taxi-location information, we can estimate the intensity of vehicles in the different regions, as shown in Table I, where Region 0 represents Beijing city as a whole. The estimation process is subdivided into the following two steps: 1) We first calculate and store the number of taxis within a circle having a radius of 60 m, which constitute a series of samples assumed to obey the Poisson distribution; and 2) then, we estimate the intensity λ according to the distribution in (1) by using the maximum likelihood method. Moreover, we run the Kolmogorov–Smirnov test (K-S test) to verify that the real data indeed satisfies the PPP. In Table II, we show the K-S test output for each region, i.e., the *P*-value. Note that for $P \geq 0.05$, the hypothesis of exponential distribution is not denied. We can see that the *P*-values of all regions are higher than 0.05, i.e., the taxi location data indeed satisfies the PPP.

Fig. 3 shows the c.d.f. of the number of vehicles within a circle of 60 m radius in different regions, where the bars represent real sample data from the dataset and the curve is the fitted PPP c.d.f. As we assumed in the system model, the spatial distribution of the real-world vehicles may be deemed reasonably consistent with the PPP distribution characteristics. Furthermore, we can observe that Region 5 representing the central area of Beijing city exhibits the highest vehicle intensity shown in Table I, while Region 7 as a suburban area has a low vehicle intensity. Moreover, the average distance between two vehicles can also be obtained from the dataset, as shown in Table I. Note that since the dataset only contains the taxi locations of Beijing city, the distances between two vehicles appear to be relatively large. In the following simulations, we will apply a multiplier of 5 to those intensities seen in Table I under the assumption that there is one taxi among five vehicles.

Based on the estimated intensity of vehicles, we can evaluate the information-sharing OP using the related parameters for the channel model listed in Table II, where the transmission power, the path loss, and fading models are configured according to [30]. Two typical scenarios are simulated: The first is the downtown scenario as in Region 1 of Beijing city, where the signal channel between two peer vehicles should obey the Nakagami-m distribution, and the second is the suburban scenario as in Region 7 of Beijing city, where the channel obeys the Rayleigh distribution. For the downtown scenario, we have to consider the effect of obstacles, such as buildings. The influence of obstacles has been modeled in the well-established simulators like Vergilius [40]–[42] or Veins [43]–[45]. In this paper, we refer to the propagation model introduced in Veins [43], where the obstacle effects $L_{\rm obs}$ were modeled by

$$L_{\rm obs}[dB] = \beta_w n_w + \gamma_w d_w \tag{29}$$

with n_w representing the number of walls that the radio wave has penetrated, d_w represents the internal dimension of a building, while β_w and γ_w represent a pair of calibration factors having a value of 9.2 dB per wall and 0.32 dB per meter [43], respectively. The building-induced blocking mostly occurs near the street intersections. Thus, we can assume the number of wall penetration occurences between two vehicles to be two, and the building's internal dimension to be 50 m. In Beijing, the average distance between two intersections is 2 km, and if we consider 50 m to be the blocked area, the percentage of building blocking can be deemed 0.025.

The estimated vehicle intensity parameters of Region 1 and Region 7 are multiplied by 5 in our simulations. Considering that the breakpoint-based path loss model is common and practical, we have simulated two path loss settings, i.e., $\alpha = 2$ and 4, which constitute a pair of common path loss parameters according to the experimental results of [30]. Thus, four cases are simulated in these two scenarios based on whether the channel's path loss is $\alpha = 2$ or 4 and whether the SNR is 10 or 20 dB, respectively. The simulations were conducted using MATLAB relying on the following procedure. The channel is first generated according to the fading distribution and to the large-scale path loss. Then, we calculate the expected probability of the SINR value being less than some threshold, given the fading and distance parameters.

Figs. 4 and 5 show the channel-induced OP of both the suburban and downtown scenarios, where the simulation results are all consistent with the theoretical results. In the downtown

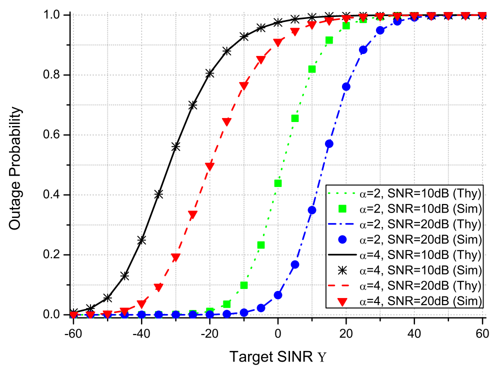

Fig. 4. Outage probability in Region 7.

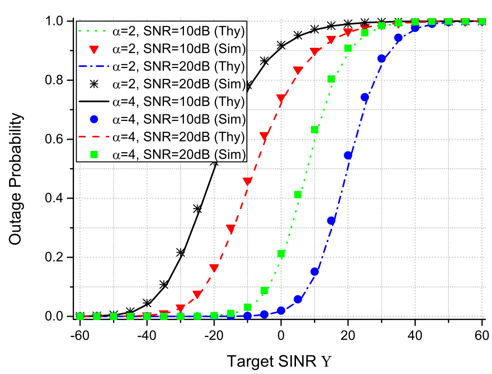

Fig. 5. Outage probability in Region 5.

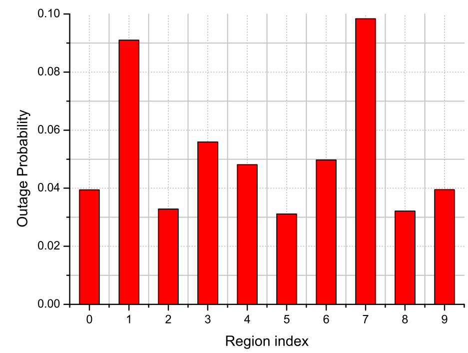

Fig. 6. Outage performance of all regions.

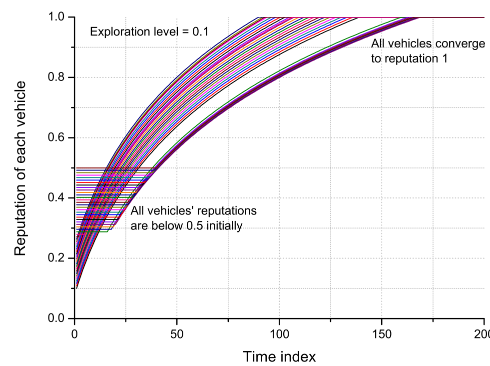

Fig. 7. Reputation of all vehicles $\xi = 0.1$.

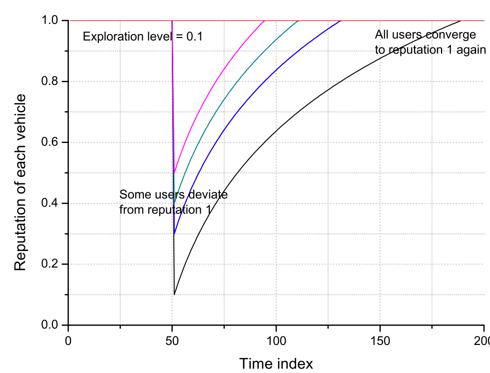

Fig. 8. Reputation of deviated vehicles $\xi = 0.1$.

scenario, the simulation results are about 1 dB worse than the theoretical results, which is due to considering the building-induced blocking effects. The curves in those two figures are quite similar, which is expected due to having the same simulation settings. The only difference is that the channel-induced OP of the downtown scenario is lower than that in the suburban scenario owing to the reduced distance between a pair of vehicles, as well as due to having benign Nakagami fading channels. Generally, we can see that increasing the path loss exponent α from 2 to 4 can lead to the increase of channel-induced OP due to the higher power attenuation of the channel, while increasing the transmission power reduces the channel-induced OP. We also simulate the information-sharing OP of other regions of Beijing city, as shown in Fig. 6, where the path loss exponent is set to $\alpha = 2$, the transmission SNR is set to 10 dB, while the target received SINR is set to $\Upsilon = -10$ dB. We can see that the information-sharing OP is proportional to the intensity of vehicles in the region. This is because a low intensity implies a higher distance between two peer vehicles and the channel attenuation is more severe. Although the low vehicular intensity can also help reduce the interference imposed by other vehicles, this positive effect is dominated by the higher channel attenuation caused by the longer prorogation distance.

Based on the information-sharing OP, we can now conduct simulations to verify the benefits of our proposed RTI sharing mechanism. We invoke Algorithm 1 over 50 vehicles, where the reputation adjustment step size was configured according to $\frac{0.02}{t}$ with t being the time index. Fig. 7 shows the dynamics of all vehicles' reputations during the learning and interaction process, which also characterizes the vehicles' information-sharing strategy. Although the vehicles are initially configured to have different reputations below 0.5, i.e., to have a relatively low reputation, the final converged all "1" reputation results corroborate the high efficiency of our credit mechanism. To further verify the stability of the proposed algorithm, we arrange for some vehicles to deviate from the converged "1" reputation, as shown in Fig. 8. It can be seen that all the vehicles that have deviated quickly converged to reputation "1" again. Note, however, that the success

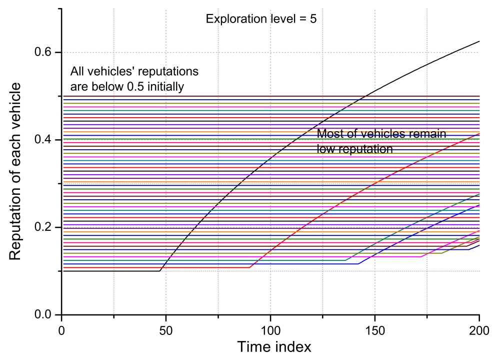

Fig. 9. Reputation of all vehicles $\xi = 5$.

of convergence is conditioned on having an appropriate setting for the exploration level. An aggressive exploration may lead to divergence, as shown in Fig. 9, where the exploration level ξ is set as high as 5. This is reasonable, because when the exploration level is excessive, the interaction probability tends to become binary according to (27), i.e., 0 or 1. In such a case, some vehicles may not have the chance to interact with others and thus may not learn the reputation of others. Therefore, how to decide on a reasonable exploration level can be a promising future research topic.

VIII. Conclusion

In this paper, we studied the RTI sharing problem in vehicular networks, including both the theoretical channel-induced OP analysis and the genuine RTI sharing mechanism design. The theoretical analysis and the simulation results lead to the following major conclusions: 1) The outage performance is closely related to the density of vehicles, where a higher density implies having a reduced distance among the vehicles, which improves the communication performance; 2) the proposed credit-based RTI sharing mechanism is effective, which can ensure that all vehicles aspire to a good reputation, when an appropriate exploration level is adopted. Future research may include the theoretical information-sharing OP analysis under other vehicular network protocols, as well as genuine RTI sharing mechanism design relying on other kinds of incentives, instead of the credit considered here.

Appendix A
Proof of Theorem 1

Following (10), we should calculate the expectation of $\mathbb{P}(\gamma_0 \le \Upsilon)$ with respect to vehicle v_1's location and channel, as well as all other v_i's locations and channels. First, let us take the expectations with respect to d_1. Since vehicle v_0 is sharing its RTI with the nearest vehicle v_1, no other vehicles can be closer than d_1, i.e., only vehicle v_0 is within the area $2Wd_1$. In this case, according to (1), the c.d.f. of d_1 can be formulated as follows:

$$\begin{aligned}&\mathbb{P}(d_1 \le D) = 1 - \mathbb{P}(d_1 > D)\\ &\quad = 1 - \mathbb{P}[\text{No other vehicle in } \pi D^2 |\text{ given the eixstence of } v_0]\\ &\quad = 1 - e^{-2\lambda W D} \end{aligned} \tag{30}$$

while the corresponding probability density function (p.d.f.) can be written as

$$f_{d_1}(d_1) = \frac{\mathrm{d}\left(1 - e^{-2\lambda W d_1}\right)}{\mathrm{d}d_1} = 2\lambda W e^{-2\lambda W d_1}. \tag{31}$$

In this case, the channel-induced OP of vehicle v_0 can be expressed as

$$\begin{aligned} p_0 &= 1 - \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}(\gamma_0 > \Upsilon)\right] f_{d_1}(d_1)\mathrm{d}d_1\\ &= 1 - \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(\frac{g_1 d_1^{-\alpha_1}}{\Lambda} > \Upsilon\right)\right] 2\lambda W e^{-2\lambda W d_1}\mathrm{d}d_1\\ &= 1 - 2\lambda W \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(g_1 > d_1^{\alpha_1}\Upsilon\Lambda\right)\right] e^{-2\lambda W d_1}\mathrm{d}d_1. \end{aligned} \tag{32}$$

Let us now concentrate our attention on the derivation of $\mathbb{E}_{g_1, g_i, d_i}[\mathbb{P}(g_1 > d_1^{\alpha_1}\Upsilon\Lambda)]$ shown in (32).

Since g_1 obeys the gamma distribution in (4), its c.d.f. can be written as

$$\begin{aligned} F_{g_1}(X) &= \mathbb{P}[g_1 \le X] = 1 - \frac{\Gamma\left(m_1, \frac{m_1}{\mu_1}X\right)}{\Gamma(m_1)}\\ &= 1 - e^{-\frac{m_1}{\mu_1}X} \sum_{k=0}^{m_1-1} \frac{1}{k!}\frac{m_1^k}{\mu_1^k} X^k \end{aligned} \tag{33}$$

where $\Gamma(\cdot,\cdot)$ is the upper incomplete gamma function, μ_1 is the mean of g_1, and the last step is valid because we assume that the Nakagami-*m* fading parameter m_1 is an integer.[1] In this case, $\mathbb{E}_{g_1, g_i, d_i}[\mathbb{P}(g_1 > d_1^{\alpha_1}\Upsilon\Lambda)]$ in (32) can be expressed as

$$\begin{aligned} &\mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(g_1 > d_1^{\alpha_1}\Upsilon\Lambda\right)\right] = \mathbb{E}_{g_i, d_i}\\ &\quad \times \left[\frac{\Gamma\left(m_1, \frac{m_1}{\mu_1}d_1^{\alpha_1}\Upsilon\Lambda\right)}{\Gamma(m_1)}\right]\\ &\quad = \mathbb{E}_{\Lambda}\left[e^{-\frac{m_1}{\mu_1}d_1^{\alpha_1}\Upsilon\Lambda} \sum_{k=0}^{m_1-1}\frac{1}{k!}\frac{m_1^k}{\mu_1^k}\left(d_1^{\alpha_1}\Upsilon\Lambda\right)^k\right]\\ &\quad = \int_0^{+\infty}\left[e^{-\frac{m_1}{\mu_1}d_1^{\alpha_1}\Upsilon\Lambda} \sum_{k=0}^{m_1-1}\frac{1}{k!}\frac{m_1^k}{\mu_1^k}\left(d_1^{\alpha_1}\Upsilon\Lambda\right)^k\right] f_{\Lambda}(\Lambda)\mathrm{d}\Lambda \end{aligned}$$

[1]When m is an integer, we have the upper incomplete gama function $\Gamma(m,x) = (m-1)!e^{-x}\sum_{k=0}^{m-1}\frac{x^k}{k!}$, the gamma function $\Gamma(m) = (m-1)!$, and $\frac{\Gamma(m, mx)}{\Gamma(m)} = e^{-mx}\sum_{k=0}^{m-1}\frac{m^k}{k!}x^k$ [46].

$$
\begin{aligned}
&= \sum_{k=0}^{m_1-1} \frac{1}{k!}\left(\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}\right)^k \int_0^{+\infty}\left[e^{-\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}\Lambda}\Lambda^k\right] f_\Lambda(\Lambda)\mathrm{d}\Lambda \\
&= \sum_{k=0}^{m_1-1} \frac{s^k}{k!}(-1)^k \frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k} \qquad (34)
\end{aligned}
$$

where $f_\Lambda(\Lambda)$ represents the p.d.f. of Λ, and $s \triangleq \frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}$, and $\mathcal{L}_\Lambda(.)$ represents the Laplace transform of the interference plus noise of vehicle v_0, while the last step exploits the property of $x^n f(x) \overset{\mathcal{L}}{\Longleftrightarrow} \frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k}$.

The Laplace transform of Λ can be calculated as follows:

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) =\ & \mathbb{E}_\Lambda\left[e^{-s\Lambda}\right] \\
=\ & e^{-s\sigma^2}\mathbb{E}_{g_i,d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} e^{-s g_i d_i^{-\alpha_2}}\right]. \qquad (35)
\end{aligned}
$$

Since all the vehicles v_i ($\forall v_i \in \mathcal{S}\backslash\{v_0, v_1\}$) are independent of each other, all the channel gains $\{g_i\}$ are i.i.d. and their locations generated independently based on the PPP are also i.i.d.; hence, (35) can be rewritten as

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) =\ & e^{-s\sigma^2}\mathbb{E}_{d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} \mathbb{E}_{g_i}\left[e^{-s g_i d_i^{-\alpha_2}}\right]\right] \\
=\ & e^{-s\sigma^2}\mathbb{E}_{d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} \frac{1}{1+s\mu_2 d_i^{-\alpha_2}}\right] \\
=\ & e^{-s\sigma^2}\exp\left(-\lambda\int_{d_1}^{+\infty}\left(1-\frac{1}{1+s\mu_2\zeta^{-\alpha_2}}\right)2W\mathrm{d}\zeta\right) \\
=\ & \exp\left(-s\sigma^2 - 2\lambda W\int_{d_1}^{+\infty}\frac{1}{1+\frac{\zeta^{\alpha_2}}{\mu_2 s}}\mathrm{d}\zeta\right) \qquad (36)
\end{aligned}
$$

where the second step is based on the assumption of experiencing a Rayleigh-fading channel with a mean of μ_2 between vehicle v_i (except for the closest vehicle v_1) and v_0. To elaborate a little further, the third step follows from the probability generating functional of the PPP [24] and the lower boundary of the integration is d_1, since the closest vehicle v_i imposing interference on vehicle v_0 should be farther than v_0's peer vehicle v_1. By invoking the following change of variables $u = \frac{\zeta}{(\mu_2 s)^{1/\alpha_2}}$ in (36), we have

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) =\ & \exp\left(-s\sigma^2 - 2\lambda W(\mu_2 s)^{1/\alpha_2}\int_{\frac{d_1}{(\mu_2 s)^{1/\alpha_2}}}^{+\infty}\frac{1}{1+u^{\alpha_2}}\mathrm{d}u\right) \\
=\ & \exp\left[-s\sigma^2 - 2\lambda W d_1 \Phi_{\alpha_2}(\mu_2 s d_1^{-\alpha_2})\right] \qquad (37)
\end{aligned}
$$

where $\Phi_\alpha(x)$ is as in (12). To summarize, by combining (32), (34), and (37), we arrive at vehicle v_0's channel-induced OP as

$$
\begin{aligned}
p_0 =\ & 1 - 2\lambda W\int_{d_1=0}^{+\infty}\sum_{k=0}^{m_1-1}\frac{(-m_1 d_1^{\alpha_2}\Upsilon)^k}{k!\mu_1^k}\frac{\mathrm{d}^k\mathcal{L}_\Lambda(s)}{\mathrm{d}s^k}\bigg|_{s=\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}} \\
& e^{-2\lambda W d_1}\mathrm{d}d_1 \qquad (38)
\end{aligned}
$$

with $\mathcal{L}_\Lambda(s)$ in (37). By setting $d_1 = \tau$, we have (11), which completes the proof of *Theorem 1*.

APPENDIX B
PROOF OF COROLLARY 1

Since Rayleigh fading is a special case of Nakagami-*m* fading associated with $m = 1$, we can calculate vehicle v_0's channel-induced OP in the highway scenario considered by setting $m_1 = 1$ and $\mu_1 = \mu_2 = \mu$ in (11), which yields

$$
\begin{aligned}
p_0^{\mathrm{hwy}_1} =\ & 1 - 2\lambda W\int_{\tau=0}^{+\infty}\mathcal{L}_\Lambda\left(\frac{\tau^{\alpha_1}\Upsilon}{\mu}\right)e^{-2\lambda W\tau}\mathrm{d}\tau \\
=\ & 1 - 2\lambda W\int_{\tau=0}^{+\infty}\exp \\
& \times\left(-\frac{\tau^{\alpha_1}\Upsilon}{\mu}\sigma^2 - 2\lambda W\int_\tau^{+\infty}\frac{1}{1+\frac{\zeta^{\alpha_2}}{\tau^{\alpha_1}\Upsilon}}\mathrm{d}\zeta\right) \\
=\ & e^{-2\lambda W\tau}\mathrm{d}\tau. \qquad (39)
\end{aligned}
$$

By employing a change of variables $u = \frac{\zeta}{\tau^{\alpha_1/\alpha_2}\Upsilon^{1/\alpha_2}}$, we can rewrite (39) as

$$
\begin{aligned}
p_0^{\mathrm{hwy}_1} =\ & 1 - 2\lambda W\int_{\tau=0}^{+\infty} e^{-2\lambda W\tau - \frac{\tau^{\alpha_1}\Upsilon}{\mu}\sigma^2 - 2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}} \\
& \times e^{\mathcal{G}_{\alpha_2}\left[\left(\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon}\right)^{\frac{1}{\alpha_2}}\right]}\mathrm{d}\tau \\
=\ & 1 - 2\lambda W\int_{\tau=0}^{+\infty}\exp\left(-\frac{\sigma^2\Upsilon}{\mu}\tau^{\alpha_1}\right) \\
& \times\exp\left[-2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}\mathcal{G}_{\alpha_2}\left(\left(\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon}\right)^{\frac{1}{\alpha_2}}\right)\right] \\
& \cdot e^{-2\lambda W\tau}\mathrm{d}\tau \qquad (40)
\end{aligned}
$$

where according to [47], we have

$$
\begin{aligned}
\mathcal{G}_\alpha(x) =\ & \int_x^{+\infty}\frac{1}{1+u^\alpha}\mathrm{d}u \\
=\ & \frac{1}{\alpha-1}\frac{x}{1+x^\alpha}\mathbf{F}\left(1,1;2-\frac{1}{\alpha};\frac{1}{1+x^\alpha}\right) \qquad (41)
\end{aligned}
$$

with the hypergeometric function given by $\mathbf{F}(a,b;c;z) = 1 + \sum_{n=1}^{+\infty}\frac{z^n}{n!}\prod_{m=0}^{n-1}\frac{(a+m)(b+m)}{c+m}$. Although (40) appears to be complicated, its physical interpretation is quite clear. The first term $\exp(-\frac{\sigma^2\Upsilon}{\mu}\tau^{\alpha_1})$ within the integration represents the channel-induced OP as a function of noise, the second term $\exp[-2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}\mathcal{G}_{\alpha_2}((\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon})^{\frac{1}{\alpha_2}})]$ represents the channel-induced OP influenced by the other vehicles v_i, and the last term $e^{-2\lambda W\tau}$ is associated with the p.d.f. of the variable $\tau = d_1$. This completes the proof of *Corollary 1*.

APPENDIX C
PROOF OF COROLLARY 2

By substituting $\alpha_1 = \alpha_2 = \alpha$ in (13), we have

$$\begin{aligned} p_0^{\mathrm{hwy}_2} &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha}\right) \cdot \\ &\quad \times \exp\left[-2\lambda W \Upsilon^{\frac{1}{\alpha}} \mathcal{G}_{\alpha}\left(\Upsilon^{-\frac{1}{\alpha}}\right)\tau\right] \cdot e^{-2\lambda W\tau}\mathrm{d}\tau \\ &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha}\right) \\ &\quad \times \exp\Big(-2\lambda W \Phi_{\alpha}(\Upsilon)\tau\Big) \cdot e^{-2\lambda W\tau}\mathrm{d}\tau \\ &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \\ &\quad \times \left[-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha} - 2\lambda W\Big(1 + \Phi_{\alpha}(\Upsilon)\Big)\tau\right]\mathrm{d}\tau \end{aligned} \tag{42}$$

where the second step is valid according to (12)

$$\Phi_{\alpha}(\Upsilon) = \Upsilon^{1/\alpha}\int_{\Upsilon^{-1/\alpha}}^{+\infty}\frac{1}{1+u^{\alpha}}\mathrm{d}u = \Upsilon^{1/\alpha}\mathcal{G}_{\alpha}\left(\Upsilon^{-1/\alpha}\right). \tag{43}$$

This completes the proof of (15) in *Corollary 2*.

Following (42), we can further consider the specific scenario of having a path loss of $\alpha = 2$, which is common in the highway vehicular network scenario of [30]. By substituting $\alpha = 2$ in (42), we have

$$\begin{aligned} p_0^{\mathrm{hwy}_2} &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{2}\right) \\ &\quad \times \exp\left(-2\lambda W \Upsilon^{\frac{1}{2}} \mathcal{G}_{2}\left(\Upsilon^{-\frac{1}{2}}\right)\tau\right) \cdot e^{-2\lambda W\tau}\mathrm{d}\tau \\ &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \\ &\quad \times \left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{2} - 2\lambda W\left(1 + \sqrt{\Upsilon}\arctan\sqrt{\Upsilon}\right)\tau\right)\mathrm{d}\tau \\ &= 1 - 2\lambda W\sqrt{\frac{\pi}{\chi_1(\Upsilon)}}\exp\left(\frac{\chi_2^2(\Upsilon)}{4\chi_1(\Upsilon)}\right) \\ &\quad \times Q\left(\frac{\chi_2(\Upsilon)}{\sqrt{2\chi_1(\Upsilon)}}\right) \end{aligned} \tag{44}$$

where the second step is valid because $\arctan(1/u) = \int_u^{+\infty}\frac{1}{1+u^2}\mathrm{d}u$ and the last step exploits the following exponential integration properties [46]:

$$\int_{\tau=0}^{+\infty}\exp(-a\tau^2 - b\tau)\mathrm{d}\tau = \sqrt{\frac{\pi}{a}}\exp\left(\frac{b^2}{4a}\right)Q\left(\frac{b}{\sqrt{2a}}\right) \tag{45}$$

with the Q-function given by $Q(x) = \frac{1}{2\pi}\int_x^{+\infty}\exp(-y^2/2)\mathrm{d}y$. This completes the proof of *Corollary 2*.

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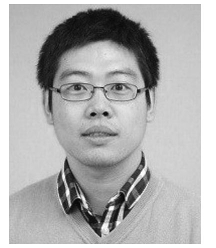

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Information-Sharing Outage-Probability Analysis of Vehicular Networks

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***Abstract*—In vehicular networks, information dissemination/sharing among vehicles is of salient importance. Although diverse mechanisms have been proposed in the existing literature, the related information credibility issues have not been investigated. Against this background, in this paper, we propose a credible information-sharing mechanism capable of ensuring that the vehicles do share genuine road traffic information (RTI). We commence with the outage-probability analysis of information sharing in vehicular networks under both a general scenario and a specific highway scenario. Closed-form expressions are derived for both scenarios, given the specific channel settings. Based on the outage-probability expressions, we formulate the utility of RTI sharing and design an algorithm for promoting the sharing of genuine RTI. To verify our theoretical analysis and the proposed mechanism, we invoke a real-world dataset containing the locations of Beijing taxis to conduct our simulations. Explicitly, our simulation results show that the spatial distribution of the vehicles obeys a Poisson point process, and our proposed credible RTI sharing mechanism is capable of ensuring that all vehicles indeed do share genuine RTI with each other.**

***Index Terms*—Credibility, information dissemination, information sharing, Poisson point process (PPP), reinforcement learning, vehicular networks.**

I. Introduction

Vehicular communications and their support networks were originally proposed for public safety applications and traffic efficiency enhancements, which necessitate reliable short-distance vehicle-to-vehicle and vehicle-to-infrastructure communications [1]. With the advent of advanced automobile technology, the globe's population has become more mobile. For example, 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 a staggering 18 h and 31 min [2]. Meanwhile, the vehicular users' demands for in-car communication have also been dramatically increasing, since a wealth of value-added services emerge such as safety message dissemination and in-car entertainment services.

Most of the existing works on information dissemination/sharing were focused on designing specific mechanisms, in particular scenarios of vehicular networks. However, the credibility of the shared road traffic information (RTI) has not been taken into account in those mechanisms. Although all the vehicles act in a cooperative manner, the selfish or malicious ones may share either random or manipulated information for the sake of attaining an unfair road priority. Hence, we consider this problem and propose a mechanism for ensuring that all vehicles share genuine RTI. Furthermore, we define the utility functions of vehicles in the RTI sharing mechanism for the sake of analyzing their incentives in the RTI sharing process, and provide a general analytical framework for the information-sharing outage probability (OP) of vehicular networks. The new contributions of this paper can be summarized as follows.

1) We derive the information-sharing OP of vehicular networks both for the general scenario modeled by Nakagami-*m* fading and for a more specific highway scenario, where Rayleigh fading is considered.
2) In order to encourage vehicles to share genuine RTI, we design a mechanism based on the reinforcement learning model, where the concept of "reputation" is introduced for circumventing the vehicles' selfish behaviors by exploiting its similarity to human social networks.
3) The real-world dataset containing the locations of Beijing taxis is utilized for verifying the vehicles' spatial distribution characteristics. Based on the parameters inferred with the aid of training from this dataset, we verify our analytical outage performance results as well as the proposed mechanism by our real-world data-driven simulations.

The rest of the paper is organized as follows. We first summarize the related works in Section II. Then, our system model is introduced in Section III. Based on the system model, the information-sharing OP is derived both for the general Nakagami-*m* as well as for the more specific Rayleigh-distributed highway scenario in Sections IV and V, respectively. In Section VI, we present the proposed RTI sharing scheme, while Section VII provides our real-world data-driven simulation results. Finally, we conclude in Section VIII.

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II. RELATED WORKS

The provision of information dissemination/sharing among vehicles is of pivotal significance in vehicular networks, which has been extensively studied in the literature [3]–[21]. Specifically, Zhao *etal.* [3] proposed an architecture and analyzed the dissemination capacity, where the data emanating from the sources were buffered by vehicles and then it was rebroadcast at the intersections. Similarly, the concept of a "smart road" was introduced and an integrated vehicular system was conceived for the collection, management, and provision of context-aware information concerning the traffic density and driver location [4].

Later, the vehicular ad hoc network (VANET) concept was proposed for assisting the dissemination of critical vehicle tracking information [5]. Meanwhile, Cenerario *et. al.* designed an event-related information exchange/sharing protocol relying on a VANET in [6]. With the goal of supporting a wide range of vehicular networks, Ros *et al.* [7] proposed a broadcast algorithm relying on periodic beacon messages, which contained acknowledgments of the circulated broadcast messages. The urban scenario of vehicular networks was studied based on the road map information as prior knowledge in [8] and relying on peer-to-peer (P2P) cooperative caching in [9]. The heterogeneity of radio propagation was taken into account in [10], where the tradeoffs amongst parameters, such as the cost, delay, and optimized system utility, were analyzed. The performance analysis of information sharing in vehicular networks was carried out in [11]–[15]. More specifically, the distribution of concurrent transmissions was analyzed in [11], while the analysis of packet loss rate and packet transmission distance was provided in [12]. The analysis of end-to-end reliability was disseminated in [13], while the throughput and delay analysis was the subject of [14] and [15].

On the other hand, the security issues of vehicular information dissemination were investigated in [16]–[18]. Explicitly, a graph-based metric was proposed for insider attacker detection in [16], whilst a trustworthiness verification model was advocated in [17] and a cooperative neighbor position verification model was conceived in [18]. Moreover, the information sharing in vehicular networks was modeled by carefully adapting the perspective of social networks [19]–[21]. Most of the aforementioned contributions were focused on designing specific mechanisms for information dissemination/sharing in particular scenarios of vehicular networks. However, the credibility of the shared RTI has not been taken into account in those mechanisms, which hence inspired this paper.

III. SYSTEM MODEL

As illustrated in Fig. 1, we consider a cooperative vehicular network constituted by a group of vehicles denoted by $\mathcal{S} = \{v_0, v_1, v_2, \ldots, v_i, \ldots\}$. Since all the vehicles are independent of each other, although their locations are geographically constrained by the mesh of roads in a city, they can be viewed as being randomly distributed. By exploiting this property, we assume that the locations of the vehicles obey a Poisson point process (PPP) on the 2-D road mesh with an intensity of λ (the number of vehicles per square kilometer). The PPP has been widely adopted for modeling the distribution of random placements, such as the locations of macrocell and femtocell base stations [22], [23], as well as of ad hoc nodes [24]. In contrast to the existing PPP model of an infinite 2-D plane, the PPP model of a vehicular network is constrained by the road-width, which may nonetheless be as wide as say 100 m in metropolitan areas. Let us denote the road-width by W, which is assumed to be a constant. Based on the PPP model, the number of vehicles in any finite rectangle having a width of W and a length of D is Poisson distributed with a mean of λA_r, which can be expressed as

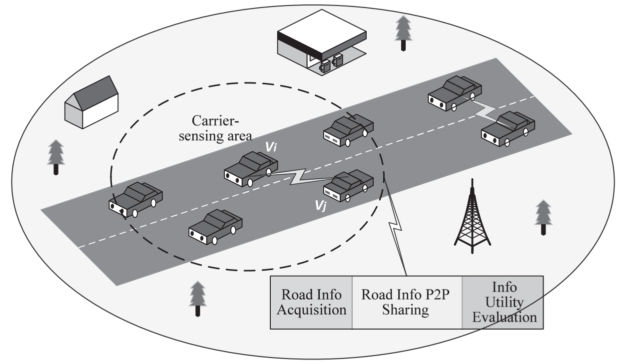

Fig. 1. System model.

$$P(N_r = n) = \frac{e^{-\lambda W D}(\lambda W D)^n}{n!}. \quad (1)$$

In our model, all the vehicles are assumed to be selfish, aiming for maximizing their own utility. We also assume that each vehicle has the capability of acquiring RTI and that they are willing to share it with each other in order to make better-informed decisions. The RTI can be for example the location information invoked for cooperative vehicle localization [25], or the traffic information invoked for cooperative route planning [26]. Our proposed model is general, and hence, it is independent of the specific form of the RTI. As shown in Fig. 1, at the beginning of each time slot, all the vehicles acquire the current RTI by their in-car sensors or by exploiting the driver's judgment. Then, each vehicle has to decide, whether it will truthfully share this information with others or whether to manipulate the shared RTI to render it useless, either, for example, due to privacy concerns or with the objective of gaining an unfair road priority. Therefore, although all the vehicles act in a cooperative manner, they occasionally may share random or manipulated information for the sake of improving their own utility. Then, each vehicle exchanges either its perceived genuine information or the false RTI with the nearest vehicle in a P2P mode. Following the information-sharing phase, each vehicle exploits its own information, as well as the shared information to make an informed decision as to whether to change speed, lanes, routes, or just maintain the current status. Finally, at the end of each time slot, the vehicle evaluates the performance attained as a result of its decision and then adjusts its actions in preparation for the next round. Here, we consider a practical scenario, where a vehicle is unable to ascertain the credibility of the RTI gleaned, until the information is actually utilized for its decision making and until the resultant performance is evaluated. Note that the time slot mentioned in this paper represents a coarse scale, on the order of seconds or minutes. Such a coarse synchronization can be readily achieved by the GPS, which has been widely deployed in vehicles. When it comes to information sharing between two vehicles, a fine-grained physical layer synchronization should be guaranteed for successful data transmission. However, such a fine-grained synchronization is not required for the entire network.

The above-mentioned P2P mode is assumed to be supported by the IEEE 802.11p protocol (a.k.a., the Wireless Access in the Vehicular Environment (WAVE)) relying on the classic Request To Send/Clear To Send (RTS/CTS) mechanism for the sake of avoiding the hidden terminal problem [27][28]. In this case, as shown in Fig. 1, only a single pair of vehicles is sharing information in a time slot within their carrier-sensing range, such as v_i and v_j. Based on this characteristic, the two-directional outage analysis is not considered in this paper, since only a single pair of vehicles is engaged in communication within the range. Nevertheless, the vehicles beyond v_i and v_j's carrier-sensing area may also impose interference on their communications according to the practical interference model of [29]. According to the experimental results of [30], the 5.9 GHz dedicated short-range communications frequency band may be modeled by a Nakagami-*m* fading channel, provided that the distance between two vehicles is below 40 m. By contrast, it is modeled by a Rayleigh-fading channel when it is above 40 m, which is a special case of the Nakagami-*m* fading associated with $m = 1$. A line-of-sight (LOS) Rician channel may also occur under certain circumstances. Nevertheless, we would like to concentrate on the Nakagami-*m* and Rayleigh-fading scenarios, especially when it comes to the metropolitan areas, where the presence of buildings and of the infrastructure may block the LOS as in Beijing city. Thus, the power received by the vehicle v_i from its peer v_j located at a distance of $d_{i,j}$ can be expressed as

$$y_{i,j} = |h_{i,j}|^2 d_{i,j}^{-\alpha_{i,j}} \tag{2}$$

where $\alpha_{i,j}$ is the channel's path loss coefficient and $h_{i,j}$ is the channel gain. Since the distance between a pair of communicating vehicles can be 40 m or higher, $h_{i,j}$ should obey the Nakagami-*m* distribution of [31]:

$$f_{h_{i,j}}(x) = 2\left(\frac{m}{\mu_{i,j}}\right)^m \frac{x^{2m-1}}{\Gamma(m)} \exp\left(-m\frac{x^2}{\mu_{i,j}}\right) \tag{3}$$

where $\Gamma(\cdot)$ is the gamma function, $\mu_{i,j} = \mathbb{E}(|h_{i,j}|^2)$ is the average received power, and m is the Nakagami-*m* fading parameter. In this paper, we only consider integer m values for the sake of mathematical tractability. Let us introduce $g_{i,j} = |h_{i,j}|^2$, where $g_{i,j}$ obeys the gamma distribution of

$$f_{g_{i,j}}(x) = \left(\frac{m}{\mu_{i,j}}\right)^m \frac{x^{m-1}}{\Gamma(m)} \exp\left(-m\frac{x}{\mu_{i,j}}\right). \tag{4}$$

When using the IEEE 802.11p protocol, all the vehicles that impose interference on the vehicle v_i in Fig. 1 should be located farther than 40 m [30]. In this case, the Rayleigh-fading model should be considered for the link imposing interference by the vehicle v_k upon v_i, i.e., $g_{i,k}$ should obey the exponential distribution of

$$f_{g_{i,k}}(x) = \frac{1}{\mu_{i,k}} \exp\left(-\frac{x}{\mu_{i,k}}\right). \tag{5}$$

IV. Channel-Induced Outage Probability in a General Scenario

In this section, we theoretically analyze the channel-induced OP of vehicular networks. The classic channel-induced OP of a specific vehicle v_i is defined as the probability of v_i's signal-to-interference-plus-noise ratio (SINR) dipping below a threshold of Υ, i.e.,

$$p_{v_i} = \mathbb{P}[\gamma_{v_i} \leq \Upsilon] \tag{6}$$

which, in fact, is also the cumulative distribution function (c.d.f) of this vehicle's SINR. Since the channel-induced OP is a physical-layer metric, the fact of whether a vehicle shares genuine or false information is irrelevant in this section. By contrast, in Section V, we will use the channel-induced OP for modeling the vehicles' future utility trend, depending on whether they are sharing genuine or false RTI.

As illustrated in the system model, we consider a P2P scenario, where every pair of closest vehicles exchange their respective RTI within each time slot. For a specific vehicle v_0, its closest counterpart v_1 should be the intended information-sharing peer. Let us denote the distance and channel gain of v_0 with respect to the transmitter of the vehicle v_1 by d_1 and g_1, respectively. Then, the SINR of the vehicle v_0 can be written as

$$\gamma_0 = \frac{g_1 d_1^{-\alpha_1}}{\Lambda} \tag{7}$$

where α_1 is the path loss coefficient, and Λ is the interference imposed by the other vehicles on the vehicle v_0 plus the noise power. Let us assume that v_1 is the vehicle closest to v_0. Then, according to the experimental results of [30], the channel gain g_1 should obey the gamma distribution as in (4) with a mean of $\mathbb{E}[g_1] = \mu_1$ and Nakagami-*m* fading parameter of m_1. During the information sharing between the pair of vehicles v_0 and v_1, the signals of all other vehicles, represented by v_i ($\forall v_i \in \mathcal{S}\backslash\{v_0, v_1\}$), should be considered as interference. Let us denote the distance and channel gain between v_i and v_0 by d_i and g_i, respectively. In this case, the interference plus noise power Λ can be calculated by

$$\Lambda = \sum_{v_i \in \mathcal{S}\backslash\{v_0, v_1\}} g_i d_i^{-\alpha_2} + \sigma^2 \tag{8}$$

where α_2 is the path loss coefficient and σ^2 is the variance of the zero-mean circularly symmetric complex-valued Gaussian noise. Assuming that the other vehicles—except for the closest one—are relatively far from v_0, Rayleigh fading prevails between v_i and v_0, i.e., the interfering channel's gain g_i obeys the exponential distribution as in (5). Since all vehicles are independent of each other, the channel gains $\{g_{i, v_i \in \mathcal{S}\backslash\{v_0, v_1\}}\}$ are independent identically distributed (i.i.d.), where $\mathbb{E}[g_{i, v_i \in \mathcal{S}\backslash\{v_0, v_1\}}] = \mu_2$. Thus, the SINR of vehicle v_0 becomes

$$\gamma_0 = \frac{g_1 d_1^{-\alpha_1}}{\sum_{v_i \in \mathcal{S} \setminus \{v_0, v_1\}} g_i d_i^{-\alpha_2} + \sigma^2} \tag{9}$$

while the channel-induced OP of vehicle v_0 in sharing information with v_1 is formulated as

$$p_0 = \mathbb{E}_{g_1, d_1, g_i, d_i} \left[\mathbb{P}(\gamma_0 \leq \Upsilon) \right]. \tag{10}$$

In the following theorem, the channel-induced OP expression of vehicle v_0 is formulated for a specific time slot.

Theorem 1: In a vehicular network relying on the 802.11p protocol and RTS/CTS, a vehicle's information-sharing OP can be expressed as

$$p_0 = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \sum_{k=0}^{m_1 - 1} \frac{(-m_1 \tau^{\alpha_2} \Upsilon)^k}{k! \mu_1^k} \left. \frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k} \right|_{s = \frac{m_1 \tau^{\alpha_1} \Upsilon}{\mu_1}} e^{-2\lambda W \tau} \mathrm{d}\tau \tag{11}$$

where the target SINR is Υ and we have

$$\Phi_\alpha(x) = x^{1/\alpha} \int_{x^{-1/\alpha}}^{+\infty} \frac{1}{1 + u^\alpha} \mathrm{d}u. \tag{12}$$

Proof: See the proof in Appendix A.

V. Information-Sharing Outage Performance in Highway Scenario

In *Theorem 1*, (11) provides the information-sharing OP of vehicular networks in a general form, which can be used in any arbitrary scenario, including both dense and sparse vehicular network scenarios. However, when considering specific application scenarios, further approximations can be adopted in the derivation of *Theorem 1*. In this section, we will consider a highway-specific scenario, where the distance amongst vehicles may be substantially higher than in the downtown area, say over 30 m on average. According to the experimental results of [30], the channel between a pair of vehicles in this highway scenario is Rayleigh fading, which implies that the channel between vehicle v_1 and v_0 is Rayleigh fading. Hence, g_1 in (7) obeys follow the exponential distribution with the same mean as g_i. In essence, this specific Rayleigh-fading highway scenario constitutes a special case of Nakagami-*m* fading associated with $m = 1$. The following corollary formulates the channel-induced OP in this highway scenario.

Corollary 1: In a highway vehicular network relying on the 802.11p protocol and RTS/CTS, a vehicle's information-sharing OP can be expressed as

$$p_0^{\mathrm{hwy}_1} = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu} \tau^{\alpha_1} \right) \cdot \exp\left[-2\lambda W \Upsilon^{\frac{1}{\alpha_2}} \tau^{\frac{\alpha_1}{\alpha_2}} \mathcal{G}_{\alpha_2}\left(\left(\frac{\tau^{\alpha_2 - \alpha_1}}{\Upsilon} \right)^{\frac{1}{\alpha_2}} \right) \right] \cdot e^{-2\lambda W \tau} \mathrm{d}\tau \tag{13}$$

where we have

$$\mathcal{G}_\alpha(x) = \int_x^{+\infty} \frac{1}{1 + u^{\alpha/2}} \mathrm{d}u. \tag{14}$$

Proof: See the proof in Appendix B.

According to the experimental results of [30], in the highway scenario the path loss measurements showed a dual-slope model, having a break-point at the distance of 100 m. When the distance between two vehicles is below 100 m, the path loss coefficient is α, while beyond 100 m it is β. Since 100 m is already at the limit of the 802.11p-based P2P information sharing, we can focus our attention on considering the scenario, where all vehicles' path loss models are identical, i.e., $\alpha_1 = \alpha_2 = \alpha$. Specifically, the experimental results of [30] showed that the path loss coefficient is $\alpha = 2$ under 100 m. The channel-induced OP of this specific scenario is formulated in the following corollary.

Corollary 2: In a highway vehicular network using the 802.11p protocol and RTS/CTS, where the path loss coefficients amongst the vehicles are identical, a vehicle's information-sharing OP can be expressed as

$$p_0^{\mathrm{hwy}_2} = 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \times \left[-\frac{\sigma^2 \Upsilon}{\mu} \tau^\alpha - 2\lambda W \Big(1 + \Phi_\alpha(\Upsilon) \Big) \tau \right] \mathrm{d}\tau. \tag{15}$$

Specifically, when the channel's path loss coefficient is $\alpha = 2$, the closed-form expression of the channel-induced OP can be formulated as

$$p_0^{\mathrm{hwy}_2} = 1 - 2\lambda W \sqrt{\frac{\pi}{\chi_1(\Upsilon)}} \exp\left(\frac{\chi_2^2(\Upsilon)}{4\chi_1(\Upsilon)} \right) \times Q\left(\frac{\chi_2(\Upsilon)}{\sqrt{2\chi_1(\Upsilon)}} \right) \tag{16}$$

where $\chi_1(\Upsilon)$ and $\chi_2(\Upsilon)$ are

$$\chi_1(\Upsilon) = \frac{\sigma^2}{\mu} \Upsilon \tag{17}$$

$$\chi_2(\Upsilon) = 2\lambda W \left(1 + \sqrt{\Upsilon} \arctan \sqrt{\Upsilon} \right). \tag{18}$$

Proof: See the proof in Appendix C.

It can be seen that (16) gives a simple closed-form expression for a single vehicle's information-sharing OP, which simply relies on the calculation of the Q-function. If we now consider the specific scenario, where the channel noise is negligible compared to the interference arriving from the other vehicles v_i, i.e., for $\sigma^2/\Lambda \to 0$, the information-sharing OP can be further simplified using the following corollary.

Corollary 3: In a highway vehicular network associated with the 802.11p protocol and RTS/CTS, where the path loss coefficients of all vehicles are identical and the channel noise is negligible compared to the interference, a vehicle's information-sharing OP during a specific time slot can be expressed as

$$p_0^{\mathrm{hwy}_3} = \frac{\Phi_\alpha(\Upsilon)}{1 + \Phi_\alpha(\Upsilon)}. \tag{19}$$

Specifically, when the channel's path loss coefficient is $\alpha = 2$, we have

$$p_0^{\mathrm{hwy}_3} = \frac{\sqrt{\Upsilon} \arctan \sqrt{\Upsilon}}{1 + \sqrt{\Upsilon} \arctan \sqrt{\Upsilon}}. \tag{20}$$

Proof: Equations (19) and (20) can be readily obtained by setting $\sigma^2 = 0$ in (15) and (16), respectively.

By now, we have completed the theoretical information-sharing OP analysis, which is an important metric that reflects whether information sharing can be reliably accomplished. Note that successful information sharing in the vehicular network relies both on successful transmission in the presence of no channel-induced outage and no genuine-information-sharing outage. Based on the channel-induced OP analysis of this section, the next section will propose a RTI sharing mechanism that ensures for the vehicles to share genuine information.

VI. Road Traffic Engineering Sharing Mechanism

In the previous section, we have studied the information-sharing OP of the vehicular network considered. Following the above performance analysis, this section will consider the vehicles' information-sharing strategies, utilities, and interactions during the RTI sharing process. Note that the sharing of RTI cannot succeed if a channel-induced outage happens between the vehicles. Let us consider a cooperative vehicular network supporting N selfish vehicles indexed as $\{v_1, v_2, ..., v_N\}$, each aiming for maximizing its own utility. As mentioned in the introduction, although all vehicles share the RTI in a cooperative manner, their specific degree of altruism/selfishness determines whether they may share false or genuine RTI for the sake of improving their own utility by exploiting unfair priority on the road for example. Considering this issue, each vehicle v_i is assumed to have a binary action space defined as follows:

$$a_i = \begin{cases} \mathbf{S}_G: & \text{sharing genuine RTI} \\ \mathbf{S}_F: & \text{sharing false RTI.} \end{cases} \tag{21}$$

As a counterpart, a mixed strategy can also be defined for vehicle v_i in which q_i represents the probability of vehicle v_i sharing genuine RTI, complemented by a $(1 - q_i)$ probability of false RTI. As mentioned in the system model, each vehicle evaluates the RTI gleaned from its peer vehicle at the end of each time slot. Additionally, we also consider a binary information reward space, where the genuine RTI earns a reward of R, while the issuance of false RTI results in a zero reward. In such a case, we can summarize vehicle v_i's utility functions as follows:

$$\begin{cases} U_{\mathrm{ij}}(\mathbf{S}_G, \mathbf{S}_G) = (1 - p_{\mathrm{ij}})R - c_i \\ U_{\mathrm{ij}}(\mathbf{S}_G, \mathbf{S}_F) = -c_i \\ U_{\mathrm{ij}}(\mathbf{S}_F, \mathbf{S}_G) = (1 - p_{\mathrm{ij}})R \\ U_{\mathrm{ij}}(\mathbf{S}_F, \mathbf{S}_F) = 0 \end{cases} \tag{22}$$

where $U_{\mathrm{ij}}(a, b)$ represents vehicle v_i's utility, when its strategy is a and its peer v_j's strategy is b with p_{ij} denoting the channel-induced OP between v_j and v_i, and $c_i > 0$ represents the additional cost of sharing genuine information. Then, $(1 - p_{\mathrm{ij}})R$ quantifies the expected reward. Additionally, it is assumed that the link's OP p_{ij} should be no higher than $1 - \frac{c_i}{R}$; otherwise, no vehicle would share genuine RTI under any circumstances.

The credit mechanism of the vehicular networks considered may be designed by observing human social networks. The concept of "reputation" is rather important for everyone in the real world, where a person's credit/reputation is generated and updated according to his/her accumulated behaviors in human social networks. Explicitly, when interacting with a reputable person, we are inclined to maintain future contacts with him/her. On the other hand, if we learned a lesson from interacting with someone having a bad reputation, a long-lasting cooperation may be unlikely. Similarly, in our cooperative vehicular network, each vehicle can evaluate the others' credit through learning from its interactions with other vehicles. In this case, a vehicle can determine whether to share its RTI with a specific vehicle according to that vehicle's credit/reputation. When a vehicle's credit is below a certain threshold, other vehicles would not share any RTI with it. It is expected that through rounds of interactions, each vehicle's credit can be gradually learned by the observations and evaluations of its shared RTI. According to this credit information, the vehicles associated with a low credit would obtain less and less shared RTI, and eventually they will have to change their RTI sharing strategy to improve their reputation. We assume that there is a central server and each vehicle can report its experience in sharing RTI with all others. As a result, the database records the vehicles' credit. The credit established by each vehicle is considered to be private information, which may not be appropriate for the server to release to the public. This is similar to our human social network, where the credit earned by each individual is not directly visible to others. Nevertheless, through rounds of interactions, one vehicle's credit can be gradually learned by others. Note that the central server is only used by the vehicles to inform the others about their RTI sharing experience and to store the credit value of each vehicle. Since the experience can be quantized to a low number of discrete levels, the amount of data related to each vehicle is relatively small. Therefore, the server does not have to maintain a large-scale database. A potential solution is that each vehicle stores its own experience and the credit values of other vehicles locally.

Similar to the human social networks, each vehicle of our vehicular network can have a credit value generated by its past behavior, and also determines its future behavior when sharing RTI with others. Let us define vehicle v_i' reputation value as r_i in conjunction with $0 \leq r_i \leq 1$. Note that in human social networks, a person's behavior is typically consistent with his/her reputation, regardless of the specific credit of the other persons he/she is interacting with. Similarly, vehicle v_i's RTI sharing strategy q_i should also be consistent with its reputation r_i, and thus these two parameters can be deemed to be identical, i.e., we have $r_i = q_i$. When v_i has the knowledge of vehicle v_j's credit/reputation through rounds of RTI sharing interactions, v_i can determine whether to cooperate with v_j in the future. Let us define v_i's interaction probability and action with respect to other vehicles as

$$\boldsymbol{\kappa}_i = [\kappa_{i1}, \kappa_{i2}, \ldots, \kappa_{\mathrm{iN}}] \tag{23}$$

$$\boldsymbol{\eta}_i = [\eta_{i1}, \eta_{i2}, \ldots, \eta_{\mathrm{iN}}] \tag{24}$$

where $0 \leq \kappa_{\mathrm{ij}} \leq 1$ represents v_i's probability of sharing RTI with v_j, regardless whether this is genuine or false information, and $\eta_{\mathrm{ij}} = 0$ or 1 represents whether or not to cooperate with v_j in a specific time slot. In such a scenario, at the beginning of each time slot, each vehicle first has to determine its next action η_{ij}, i.e., whether to cooperate with the nearest vehicle v_j, according to v_i's interaction probability κ_{ij}. Then, if it has decided to share RTI with v_j, it has to further determine the RTI sharing action a_i, i.e., as to whether to share genuine or false RTI with a specific peer vehicle, according to both v_i's information-sharing strategy q_i as well as to its reputation r_i.

Meanwhile, after rounds of RTI sharing interactions, vehicle v_i should update its interaction probability $\boldsymbol{\kappa}_i$ according to its experience with the others or by querying the database. It is expected that through a series of alternating decision making and learning processes, the vehicles having a bad reputation would obtain decreasingly less shared RTI from the others, and thus they would have to ameliorate their credit/reputation by actively sharing genuine RTI hereafter.

During the multiround RTI sharing process, none of the vehicles has access to the other vehicles' information-sharing strategies, actions, and utilities. Moreover, due to the rapidly evolving topology of vehicular networks, each vehicle may share its RTI with different vehicles during different time slots. Hence, from an individual vehicle's perspective, the network including all other vehicles can be regarded as an external environment, within which the vehicle makes decisions and shares RTI with the goal of maximizing its own utility. Generally, each vehicle learns from its interactions with this dynamic environment and adapts to the environment by adjusting its strategies for the sake of gleaning an increased utility. Reinforcement learning is a powerful tool capable of solving such an adaptive environment-learning and decision-making problem [32]. Its actions are reminiscent of how an intelligent agent infers the unknown statistical features of its environment as well as its actions in the environment so as to maximize a certain notion of the cumulative reward, where the environment itself is gradually changed by the agent's actions. Reinforcement learning has been widely adopted in communications and networks [33], [34], control [35], finance, and economics [36], as well as in social science [37], [38].

In our model, one of the main technical problems is how each vehicle constructs its interaction probability vector $\boldsymbol{\kappa}_i$ after rounds of RTI sharing interactions with the others. Based on the reinforcement learning model, each vehicle should first construct its perception through learning the others' inclination in RTI sharing. The *perception* is a quantitative representation of the accumulated utilities, which records all the historical interactions of the past as well as the new interaction results. In other words, it relies on the exploitation of past knowledge and on the exploration of a new environment [32]. Let us define vehicle v_i's perception of the others' behaviors as $\mathbf{z}_i$, where

$$\mathbf{z}_i = [z_{i1}, z_{i2}, \ldots, z_{i\mathrm{N}}] \tag{25}$$

with z_{ij} being vehicle v_i's perception with respect to v_j. At the end of each time slot, v_i first evaluates the utility of information received from v_j and then utilizes this utility value for adjusting its perception associated with v_j, while keeping the perception of others unchanged, which can be expressed as

$$z_{\mathrm{ij}}^{t+1} = \begin{cases} (1-\epsilon_i^t) z_{\mathrm{ij}}^t + \epsilon_i^t U_{\mathrm{ij}}^t, & \text{if } \eta_{\mathrm{ij}}^t = 1 \\ z_{\mathrm{ij}}^t, & \text{if } \eta_{\mathrm{ij}}^t = 0 \end{cases} \tag{26}$$

where the superscript t represents the time slot, U_{ij}^t is v_i's utility gleaned through exchanging information with v_j during time slot t, and ϵ_i^t is a sequence of averaging factors controlling the rate of decay in conjunction with $\sum_t \epsilon_i^t = \infty$ and $\sum_t (\epsilon_i^t)^2 < \infty$. The constraint of $\sum_t \epsilon^t = \infty$ is imposed for ensuring $\epsilon^t > 0$, i.e., the new learned utility U_{ij}^t should always be incorporated. By contrast, the constraint of $\sum_t (\epsilon^t)^2 < \infty$ is used for ensuring $\epsilon^t < 1$, i.e., the history of the learned experience z_{ij}^t should always be utilized.

After updating the perception $\mathbf{z}_i$, vehicle v_i can utilize it for generating its interaction probability with respect to vehicle v_j. Apparently, the more utility v_i can obtain through sharing RTI with vehicle v_j, the higher the interaction probability κ_{ij} should be, which represents a proportional relationship between κ_{ij} and z_{ij}. Here, we adopt a normalized performance evaluation method based on the *Boltzmann* exploration rule formulated as follows [32]:

$$\kappa_{\mathrm{ij}}^t = \frac{e^{\xi_i^t z_{\mathrm{ij}}^t}}{\max\{e^{\xi_i^t z_{\mathrm{ij}}^t}, \forall j\}} \tag{27}$$

where the positive coefficient ξ_j^t controls the exploration level with $\xi_j^t \to 0$ leading to a 0.5 interaction probability, while for $\xi_j^t \to \infty$ the action would concentrate only on one of the pure unconditional cooperation or no cooperation strategy, whichever results in a higher perception. The physical meaning of (27) is that vehicle v_i always shares RTI with that specific vehicle, which can give v_i the highest utility. Then, v_i considers this highest utility as a reference, when it determines its interaction probability with others.

To summarize, the reinforcement learning-based credible RTI sharing scheme can be interpreted as a process, in which each vehicle learns about its utilities as well as perceptions, and then updates its estimation regarding the other vehicles' reputation as well as adjusts its interaction behavior accordingly using its accumulated perception. The evolution from z_{ij}^t to z_{ij}^{t+1} can be illustrated by a chain of iterative elementary steps: the initial perception gives rise to a random interaction probability that determines the interaction; by following the interaction and the information-sharing action, the resultant utility is evaluated and then the perception can be updated in the next round, and so on. The iterations can be simply expressed by the following illustrative chain:

$$\begin{array}{ccccccccc} z_{\mathrm{ij}}^t & \to & \kappa_{\mathrm{ij}}^t & \to & \eta_{\mathrm{ij}}^t & \to & U_{\mathrm{ij}}^t & \to & z_{\mathrm{ij}}^{t+1} \\ & & \downarrow & & & & \uparrow & & \\ & & r_i^t & \to & q_i^t & \to & a_i^t & & \end{array} \tag{28}$$

where the arrow between κ_{ij}^t and r_i^t means that when a vehicle discovers that the number of other vehicles sharing RTI with it is less than a certain threshold, the vehicle would consider to increase its credit value in order to enhance its reputation by

Algorithm 1: Credit mechanism for RTI sharing.

for each vehicle v_i **do**
  /********** *Initialization* **********/
  Initialize v_i's credit value r_i^0 and credit adjustment step size Δr_i.
  Initialize v_i's perception $\mathbf{z}_i^0 = \mathbf{0}$.
  Initialize v_i's interaction probability $\boldsymbol{\kappa}_i^0 = \mathbf{1}$.
  Initialize the number of v_i's cooperative vehicles $n_i^0 = 0$ and the threshold n_{th}.
  Setup the learning speed ϵ_i, the exploration level ξ_i and the tolerance ζ.
  /********** *RTI sharing interaction* **********/
  for each time slot t **do**
    Discover the nearest vehicle v_j.
    Determine η_{ij}^t using random number generator $\mathbf{rand}(\kappa_{\text{ij}}^t)$.
    /********** *Perception adjustment* **********/
    if $\eta_{\text{ij}}^t == 1$ **then**
      Set $s_i^t = r_i^t$ and the RTI sharing action a_i^t using $\mathbf{rand}(q_i^t)$.
      RTI sharing, evaluate the information utility U_{ij}^t.
      Update v_i's perception z_{ij}^t and store n_i^t.
    end if
    /********** *Interaction probability adjustment* **********/
    if $\left(z_{\text{ij}}^t - z_{\text{ij}}^{(t-1)}\right)^2 \geq \zeta$ **then**
      Updatev_i's interaction probability $\kappa_{\text{ij}}^t = e^{\xi_i^t z_{\text{ij}}^t} / \max\{e^{\xi_i^t z_{\text{ij}}^t}, \forall j\}$.
    end if
    /********** *Reputation adjustment* **********/
    if $\frac{1}{t}\sum_t n_i^t < n_{\text{th}}$ **then**
      $r_i = r_i + \Delta r_i$.
    end if
    $t = t + 1$.
  end for
end for

sharing more genuine RTI with the others. The credit mechanism is summarized in Algorithm 1. In the initialization phase, each vehicle may have different prior credit vales and credit adjustment preference. Meanwhile, the learning speed ϵ determines the weight of new information, the exploration level ξ determines the probability of adopting uncharted strategies, while the tolerance determines the learning performance. In the RTI sharing phase, each vehicle first connects with the nearest vehicle and generates the interaction strategy, i.e., whether to interact with the vehicle. If the interaction indicator is positive, the vehicle then shares the genuine RTI with a probability generated by its reputation. Following the information-sharing interaction, the vehicle evaluates its perception and updates the interaction probability in the next round. If the vehicle finds that the number of other vehicles who would like to exchange information with it is below some threshold, the vehicle would adjust its reputation according to the preferred adjustment step size. In the next section, we will conduct simulations to quantify the performance of the proposed algorithm.

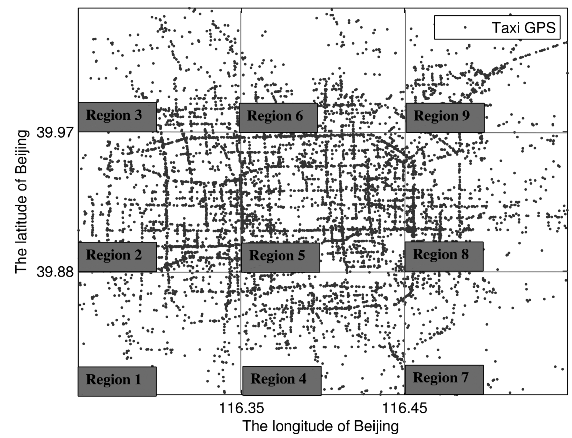

Fig. 2. Locations of Beijing taxis.

TABLE I
VEHICLE INTENSITIES OF DIFFERENT REGIONS AT BEIJING

Region	0	1	2	3	4
Intensity (/km^2)	59.6	23.3	72.7	40.7	48.1
Average distance (m)	89.03	227.79	73.01	130.41	110.42
K-S test (*P*-value)	0.0731	0.1179	0.1061	0.0705	0.0619
Region	5	6	7	8	9
Intensity (/km^2)	76.8	46.3	21.2	74.4	59.6
Average distance (m)	69.12	114.57	250.00	71.35	89.05
K-S test (*P*-value)	0.1169	0.0774	0.0831	0.0584	0.0937

TABLE II
NUMERICAL PARAMETERS FOR PERFORMANCE EVALUATION

Parameter	Value
Max Tx Power	20 dBm
Antennas	1 Tx, 1 Rx
Antennas gains	5 dBm
Nakagami-*m* fading parameter	$m = 2$
Path loss exponent	$\alpha = 2, 4$
Noise power	$\sigma^2 = 0.1$ dBm
Maximum OP	$\Upsilon = 0.1$

VII. SIMULATION RESULTS BASED ON REAL TRAFFIC DATA

In this section, we conduct simulations to verify our theoretical analysis and characterize the proposed schemes. The simulations are based on a real-world dataset consisting of the spatial distribution of Beijing taxis. In the following, we will first estimate the intensity of the taxis in Beijing using the dataset. Then, based on the estimated intensity, we will characterize the outage performance of RTI sharing as well as verify the merits of the proposed RTI sharing scheme.

The real-world dataset contains the GPS positions of 10 258 taxis in Beijing (longitude from 116.25 to 116.55 and latitude from 39.8 to 40.05) during the period of February 2–8, 2008 [39]. As shown in Fig. 2, the positions of these vehicles at a

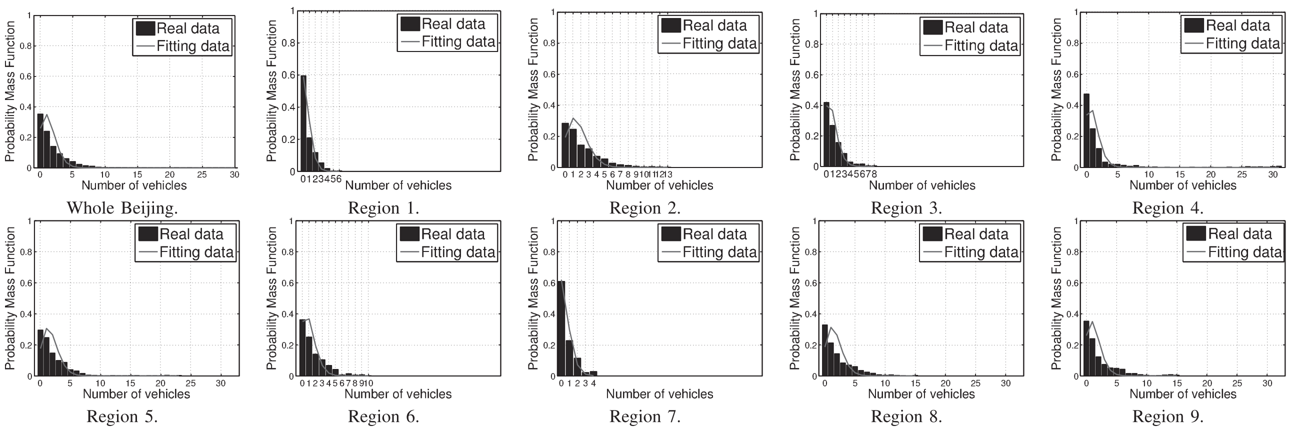

Fig. 3. Taxis position distributions of different regions at Beijing.

specific time instant are illustrated. We can see that the vehicles' position distribution reflects the planning structure of Beijing. Furthermore, we can distinguish the downtown and suburban areas. For the sake of illustrating the specific regional characteristics, instead of painting a picture of the whole city, we separate Beijing city into nine regions, as shown in Fig. 2. Based on the taxi-location information, we can estimate the intensity of vehicles in the different regions, as shown in Table I, where Region 0 represents Beijing city as a whole. The estimation process is subdivided into the following two steps: 1) We first calculate and store the number of taxis within a circle having a radius of 60 m, which constitute a series of samples assumed to obey the Poisson distribution; and 2) then, we estimate the intensity λ according to the distribution in (1) by using the maximum likelihood method. Moreover, we run the Kolmogorov–Smirnov test (K-S test) to verify that the real data indeed satisfies the PPP. In Table II, we show the K-S test output for each region, i.e., the *P*-value. Note that for $P \geq 0.05$, the hypothesis of exponential distribution is not denied. We can see that the *P*-values of all regions are higher than 0.05, i.e., the taxi location data indeed satisfies the PPP.

Fig. 3 shows the c.d.f. of the number of vehicles within a circle of 60 m radius in different regions, where the bars represent real sample data from the dataset and the curve is the fitted PPP c.d.f. As we assumed in the system model, the spatial distribution of the real-world vehicles may be deemed reasonably consistent with the PPP distribution characteristics. Furthermore, we can observe that Region 5 representing the central area of Beijing city exhibits the highest vehicle intensity shown in Table I, while Region 7 as a suburban area has a low vehicle intensity. Moreover, the average distance between two vehicles can also be obtained from the dataset, as shown in Table I. Note that since the dataset only contains the taxi locations of Beijing city, the distances between two vehicles appear to be relatively large. In the following simulations, we will apply a multiplier of 5 to those intensities seen in Table I under the assumption that there is one taxi among five vehicles.

Based on the estimated intensity of vehicles, we can evaluate the information-sharing OP using the related parameters for the channel model listed in Table II, where the transmission power, the path loss, and fading models are configured according to [30]. Two typical scenarios are simulated: The first is the downtown scenario as in Region 1 of Beijing city, where the signal channel between two peer vehicles should obey the Nakagami-*m* distribution, and the second is the suburban scenario as in Region 7 of Beijing city, where the channel obeys the Rayleigh distribution. For the downtown scenario, we have to consider the effect of obstacles, such as buildings. The influence of obstacles has been modeled in the well-established simulators like Vergilius [40]–[42] or Veins [43]–[45]. In this paper, we refer to the propagation model introduced in Veins [43], where the obstacle effects $L_{\rm obs}$ were modeled by

$$L_{\rm obs}[dB] = \beta_w n_w + \gamma_w d_w \tag{29}$$

with n_w representing the number of walls that the radio wave has penetrated, d_w represents the internal dimension of a building, while β_w and γ_w represent a pair of calibration factors having a value of 9.2 dB per wall and 0.32 dB per meter [43], respectively. The building-induced blocking mostly occurs near the street intersections. Thus, we can assume the number of wall penetration occurences between two vehicles to be two, and the building's internal dimension to be 50 m. In Beijing, the average distance between two intersections is 2 km, and if we consider 50 m to be the blocked area, the percentage of building blocking can be deemed 0.025.

The estimated vehicle intensity parameters of Region 1 and Region 7 are multiplied by 5 in our simulations. Considering that the breakpoint-based path loss model is common and practical, we have simulated two path loss settings, i.e., $\alpha = 2$ and 4, which constitute a pair of common path loss parameters according to the experimental results of [30]. Thus, four cases are simulated in these two scenarios based on whether the channel's path loss is $\alpha = 2$ or 4 and whether the SNR is 10 or 20 dB, respectively. The simulations were conducted using MATLAB relying on the following procedure. The channel is first generated according to the fading distribution and to the large-scale path loss. Then, we calculate the expected probability of the SINR value being less than some threshold, given the fading and distance parameters.

Figs. 4 and 5 show the channel-induced OP of both the suburban and downtown scenarios, where the simulation results are all consistent with the theoretical results. In the downtown

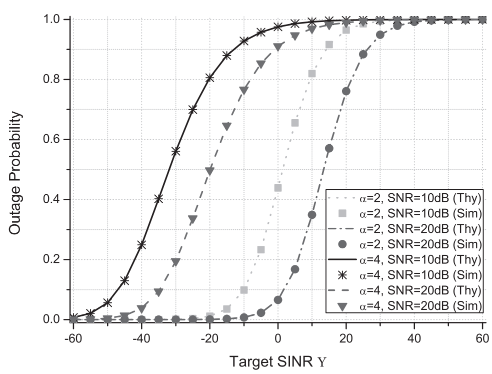

Fig. 4. Outage probability in Region 7.

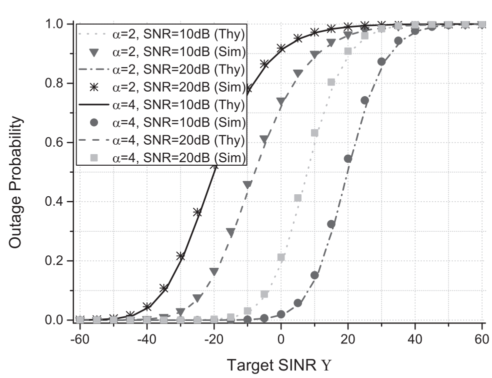

Fig. 5. Outage probability in Region 5.

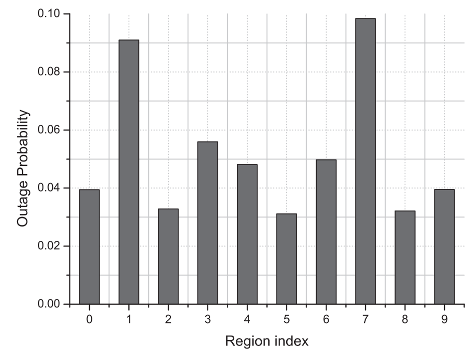

Fig. 6. Outage performance of all regions.

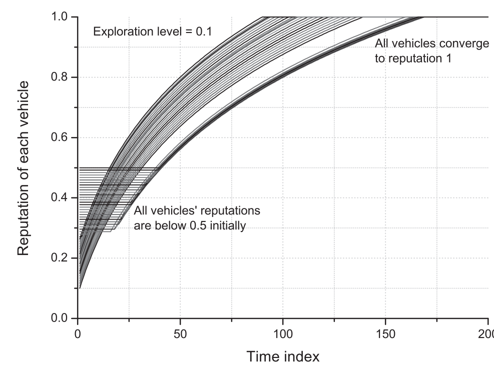

Fig. 7. Reputation of all vehicles $\xi = 0.1$.

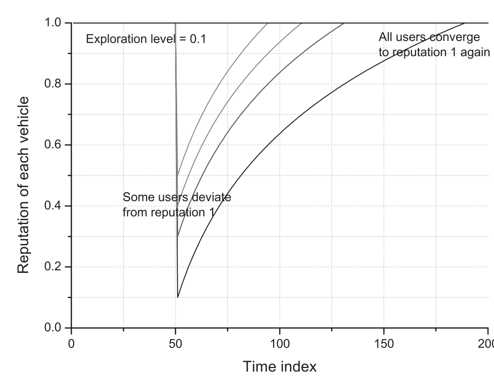

Fig. 8. Reputation of deviated vehicles $\xi = 0.1$.

scenario, the simulation results are about 1 dB worse than the theoretical results, which is due to considering the building-induced blocking effects. The curves in those two figures are quite similar, which is expected due to having the same simulation settings. The only difference is that the channel-induced OP of the downtown scenario is lower than that in the suburban scenario owing to the reduced distance between a pair of vehicles, as well as due to having benign Nakagami fading channels. Generally, we can see that increasing the path loss exponent α from 2 to 4 can lead to the increase of channel-induced OP due to the higher power attenuation of the channel, while increasing the transmission power reduces the channel-induced OP. We also simulate the information-sharing OP of other regions of Beijing city, as shown in Fig. 6, where the path loss exponent is set to $\alpha = 2$, the transmission SNR is set to 10 dB, while the target received SINR is set to $\Upsilon = -10$ dB. We can see that the information-sharing OP is proportional to the intensity of vehicles in the region. This is because a low intensity implies a higher distance between two peer vehicles and the channel attenuation is more severe. Although the low vehicular intensity can also help reduce the interference imposed by other vehicles, this positive effect is dominated by the higher channel attenuation caused by the longer prorogation distance.

Based on the information-sharing OP, we can now conduct simulations to verify the benefits of our proposed RTI sharing mechanism. We invoke Algorithm 1 over 50 vehicles, where the reputation adjustment step size was configured according to $\frac{0.02}{t}$ with t being the time index. Fig. 7 shows the dynamics of all vehicles' reputations during the learning and interaction process, which also characterizes the vehicles' information-sharing strategy. Although the vehicles are initially configured to have different reputations below 0.5, i.e., to have a relatively low reputation, the final converged all "1" reputation results corroborate the high efficiency of our credit mechanism. To further verify the stability of the proposed algorithm, we arrange for some vehicles to deviate from the converged "1" reputation, as shown in Fig. 8. It can be seen that all the vehicles that have deviated quickly converged to reputation "1" again. Note, however, that the success

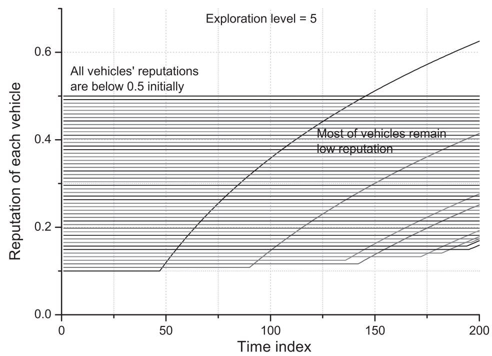

Fig. 9. Reputation of all vehicles $\xi = 5$.

of convergence is conditioned on having an appropriate setting for the exploration level. An aggressive exploration may lead to divergence, as shown in Fig. 9, where the exploration level ξ is set as high as 5. This is reasonable, because when the exploration level is excessive, the interaction probability tends to become binary according to (27), i.e., 0 or 1. In such a case, some vehicles may not have the chance to interact with others and thus may not learn the reputation of others. Therefore, how to decide on a reasonable exploration level can be a promising future research topic.

VIII. Conclusion

In this paper, we studied the RTI sharing problem in vehicular networks, including both the theoretical channel-induced OP analysis and the genuine RTI sharing mechanism design. The theoretical analysis and the simulation results lead to the following major conclusions: 1) The outage performance is closely related to the density of vehicles, where a higher density implies having a reduced distance among the vehicles, which improves the communication performance; 2) the proposed credit-based RTI sharing mechanism is effective, which can ensure that all vehicles aspire to a good reputation, when an appropriate exploration level is adopted. Future research may include the theoretical information-sharing OP analysis under other vehicular network protocols, as well as genuine RTI sharing mechanism design relying on other kinds of incentives, instead of the credit considered here.

Appendix A
Proof of Theorem 1

Following (10), we should calculate the expectation of $\mathbb{P}(\gamma_0 \le \Upsilon)$ with respect to vehicle v_1's location and channel, as well as all other v_i's locations and channels. First, let us take the expectations with respect to d_1. Since vehicle v_0 is sharing its RTI with the nearest vehicle v_1, no other vehicles can be closer than d_1, i.e., only vehicle v_0 is within the area $2Wd_1$. In this case, according to (1), the c.d.f. of d_1 can be formulated as follows:

$$\begin{aligned}&\mathbb{P}(d_1 \le D) = 1 - \mathbb{P}(d_1 > D)\\&= 1 - \mathbb{P}[\text{No other vehicle in } \pi D^2 | \text{ given the eixstence of } v_0]\\&= 1 - e^{-2\lambda W D}\end{aligned} \tag{30}$$

while the corresponding probability density function (p.d.f.) can be written as

$$f_{d_1}(d_1) = \frac{\mathrm{d}\left(1 - e^{-2\lambda W d_1}\right)}{\mathrm{d}d_1} = 2\lambda W e^{-2\lambda W d_1}. \tag{31}$$

In this case, the channel-induced OP of vehicle v_0 can be expressed as

$$\begin{aligned}p_0 &= 1 - \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}(\gamma_0 > \Upsilon)\right] f_{d_1}(d_1)\mathrm{d}d_1\\&= 1 - \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(\frac{g_1 d_1^{-\alpha_1}}{\Lambda} > \Upsilon\right)\right] 2\lambda W e^{-2\lambda W d_1}\mathrm{d}d_1\\&= 1 - 2\lambda W \int_{d_1=0}^{+\infty} \mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(g_1 > d_1^{\alpha_1}\Upsilon\Lambda\right)\right] e^{-2\lambda W d_1}\mathrm{d}d_1.\end{aligned} \tag{32}$$

Let us now concentrate our attention on the derivation of $\mathbb{E}_{g_1, g_i, d_i}[\mathbb{P}(g_1 > d_1^{\alpha_1}\Upsilon\Lambda)]$ shown in (32).

Since g_1 obeys the gamma distribution in (4), its c.d.f. can be written as

$$\begin{aligned}F_{g_1}(X) &= \mathbb{P}[g_1 \le X] = 1 - \frac{\Gamma\left(m_1, \frac{m_1}{\mu_1}X\right)}{\Gamma(m_1)}\\&= 1 - e^{-\frac{m_1}{\mu_1}X} \sum_{k=0}^{m_1-1} \frac{1}{k!}\frac{m_1^k}{\mu_1^k} X^k\end{aligned} \tag{33}$$

where $\Gamma(\cdot,\cdot)$ is the upper incomplete gamma function, μ_1 is the mean of g_1, and the last step is valid because we assume that the Nakagami-*m* fading parameter m_1 is an integer.[1] In this case, $\mathbb{E}_{g_1, g_i, d_i}[\mathbb{P}(g_1 > d_1^{\alpha_1}\Upsilon\Lambda)]$ in (32) can be expressed as

$$\begin{aligned}&\mathbb{E}_{g_1, g_i, d_i}\left[\mathbb{P}\left(g_1 > d_1^{\alpha_1}\Upsilon\Lambda\right)\right] = \mathbb{E}_{g_i, d_i}\\&\quad\times \left[\frac{\Gamma\left(m_1, \frac{m_1}{\mu_1} d_1^{\alpha_1}\Upsilon\Lambda\right)}{\Gamma(m_1)}\right]\\&= \mathbb{E}_{\Lambda}\left[e^{-\frac{m_1}{\mu_1} d_1^{\alpha_1}\Upsilon\Lambda} \sum_{k=0}^{m_1-1} \frac{1}{k!}\frac{m_1^k}{\mu_1^k}\left(d_1^{\alpha_1}\Upsilon\Lambda\right)^k\right]\\&= \int_0^{+\infty}\left[e^{-\frac{m_1}{\mu_1} d_1^{\alpha_1}\Upsilon\Lambda} \sum_{k=0}^{m_1-1} \frac{1}{k!}\frac{m_1^k}{\mu_1^k}\left(d_1^{\alpha_1}\Upsilon\Lambda\right)^k\right] f_{\Lambda}(\Lambda)\mathrm{d}\Lambda\end{aligned}$$

[1]When m is an integer, we have the upper incomplete gama function $\Gamma(m, x) = (m-1)! e^{-x} \sum_{k=0}^{m-1} \frac{x^k}{k!}$, the gamma function $\Gamma(m) = (m-1)!$, and $\frac{\Gamma(m, mx)}{\Gamma(m)} = e^{-mx} \sum_{k=0}^{m-1} \frac{m^k}{k!} x^k$ [46].

$$
\begin{aligned}
&= \sum_{k=0}^{m_1-1} \frac{1}{k!}\left(\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}\right)^k \int_0^{+\infty}\left[e^{-\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}\Lambda}\Lambda^k\right] f_\Lambda(\Lambda)\mathrm{d}\Lambda \\
&= \sum_{k=0}^{m_1-1} \frac{s^k}{k!}(-1)^k \frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k} \qquad (34)
\end{aligned}
$$

where $f_\Lambda(\Lambda)$ represents the p.d.f. of Λ, and $s \triangleq \frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}$, and $\mathcal{L}_\Lambda(.)$ represents the Laplace transform of the interference plus noise of vehicle v_0, while the last step exploits the property of $x^n f(x) \overset{\mathcal{L}}{\Longleftrightarrow} \frac{\mathrm{d}^k \mathcal{L}_\Lambda(s)}{\mathrm{d}s^k}$.

The Laplace transform of Λ can be calculated as follows:

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) &= \mathbb{E}_\Lambda\left[e^{-s\Lambda}\right] \\
&= e^{-s\sigma^2}\mathbb{E}_{g_i,d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} e^{-s g_i d_i^{-\alpha_2}}\right]. \qquad (35)
\end{aligned}
$$

Since all the vehicles v_i $(\forall v_i \in \mathcal{S}\backslash\{v_0, v_1\})$ are independent of each other, all the channel gains $\{g_i\}$ are i.i.d. and their locations generated independently based on the PPP are also i.i.d.; hence, (35) can be rewritten as

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) &= e^{-s\sigma^2}\mathbb{E}_{d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} \mathbb{E}_{g_i}\left[e^{-s g_i d_i^{-\alpha_2}}\right]\right] \\
&= e^{-s\sigma^2}\mathbb{E}_{d_i}\left[\prod_{v_i\in\mathcal{S}\backslash\{v_0,v_1\}} \frac{1}{1+s\mu_2 d_i^{-\alpha_2}}\right] \\
&= e^{-s\sigma^2}\exp\left(-\lambda\int_{d_1}^{+\infty}\left(1-\frac{1}{1+s\mu_2\zeta^{-\alpha_2}}\right)2W\mathrm{d}\zeta\right) \\
&= \exp\left(-s\sigma^2 - 2\lambda W\int_{d_1}^{+\infty}\frac{1}{1+\frac{\zeta^{\alpha_2}}{\mu_2 s}}\mathrm{d}\zeta\right) \qquad (36)
\end{aligned}
$$

where the second step is based on the assumption of experiencing a Rayleigh-fading channel with a mean of μ_2 between vehicle v_i (except for the closest vehicle v_1) and v_0. To elaborate a little further, the third step follows from the probability generating functional of the PPP [24] and the lower boundary of the integration is d_1, since the closest vehicle v_i imposing interference on vehicle v_0 should be farther than v_0's peer vehicle v_1. By invoking the following change of variables $u = \frac{\zeta}{(\mu_2 s)^{1/\alpha_2}}$ in (36), we have

$$
\begin{aligned}
\mathcal{L}_\Lambda(s) &= \exp\left(-s\sigma^2 - 2\lambda W(\mu_2 s)^{1/\alpha_2}\int_{\frac{d_1}{(\mu_2 s)^{1/\alpha_2}}}^{+\infty}\frac{1}{1+u^{\alpha_2}}\mathrm{d}u\right) \\
&= \exp\left[-s\sigma^2 - 2\lambda W d_1 \Phi_{\alpha_2}(\mu_2 s d_1^{-\alpha_2})\right] \qquad (37)
\end{aligned}
$$

where $\Phi_\alpha(x)$ is as in (12). To summarize, by combining (32), (34), and (37), we arrive at vehicle v_0's channel-induced OP as

$$
p_0 = 1 - 2\lambda W\int_{d_1=0}^{+\infty}\sum_{k=0}^{m_1-1}\frac{(-m_1 d_1^{\alpha_2}\Upsilon)^k}{k!\mu_1^k}\frac{\mathrm{d}^k\mathcal{L}_\Lambda(s)}{\mathrm{d}s^k}\bigg|_{s=\frac{m_1 d_1^{\alpha_1}\Upsilon}{\mu_1}} e^{-2\lambda W d_1}\mathrm{d}d_1 \qquad (38)
$$

with $\mathcal{L}_\Lambda(s)$ in (37). By setting $d_1 = \tau$, we have (11), which completes the proof of *Theorem 1*.

Appendix B
Proof of Corollary 1

Since Rayleigh fading is a special case of Nakagami-*m* fading associated with $m = 1$, we can calculate vehicle v_0's channel-induced OP in the highway scenario considered by setting $m_1 = 1$ and $\mu_1 = \mu_2 = \mu$ in (11), which yields

$$
\begin{aligned}
p_0^{\text{hwy}_1} &= 1 - 2\lambda W\int_{\tau=0}^{+\infty}\mathcal{L}_\Lambda\left(\frac{\tau^{\alpha_1}\Upsilon}{\mu}\right)e^{-2\lambda W\tau}\mathrm{d}\tau \\
&= 1 - 2\lambda W\int_{\tau=0}^{+\infty}\exp \\
&\quad\times\left(-\frac{\tau^{\alpha_1}\Upsilon}{\mu}\sigma^2 - 2\lambda W\int_\tau^{+\infty}\frac{1}{1+\frac{\zeta^{\alpha_2}}{\tau^{\alpha_1}\Upsilon}}\mathrm{d}\zeta\right) \\
&= e^{-2\lambda W\tau}\mathrm{d}\tau. \qquad (39)
\end{aligned}
$$

By employing a change of variables $u = \frac{\zeta}{\tau^{\alpha_1/\alpha_2}\Upsilon^{1/\alpha_2}}$, we can rewrite (39) as

$$
\begin{aligned}
p_0^{\text{hwy}_1} &= 1 - 2\lambda W\int_{\tau=0}^{+\infty} e^{-2\lambda W\tau - \frac{\tau^{\alpha_1}\Upsilon}{\mu}\sigma^2 - 2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}} \\
&\quad\times e^{\mathcal{G}_{\alpha_2}\left[\left(\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon}\right)^{\frac{1}{\alpha_2}}\right]}\mathrm{d}\tau \\
&= 1 - 2\lambda W\int_{\tau=0}^{+\infty}\exp\left(-\frac{\sigma^2\Upsilon}{\mu}\tau^{\alpha_1}\right) \\
&\quad\times\exp\left[-2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}\mathcal{G}_{\alpha_2}\left(\left(\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon}\right)^{\frac{1}{\alpha_2}}\right)\right] \\
&\quad\cdot e^{-2\lambda W\tau}\mathrm{d}\tau \qquad (40)
\end{aligned}
$$

where according to [47], we have

$$
\begin{aligned}
\mathcal{G}_\alpha(x) &= \int_x^{+\infty}\frac{1}{1+u^\alpha}\mathrm{d}u \\
&= \frac{1}{\alpha-1}\frac{x}{1+x^\alpha}\mathbf{F}\left(1,1;2-\frac{1}{\alpha};\frac{1}{1+x^\alpha}\right) \qquad (41)
\end{aligned}
$$

with the hypergeometric function given by $\mathbf{F}(a,b;c;z) = 1 + \sum_{n=1}^{+\infty}\frac{z^n}{n!}\prod_{m=0}^{n-1}\frac{(a+m)(b+m)}{c+m}$. Although (40) appears to be complicated, its physical interpretation is quite clear. The first term $\exp(-\frac{\sigma^2\Upsilon}{\mu}\tau^{\alpha_1})$ within the integration represents the channel-induced OP as a function of noise, the second term $\exp[-2\lambda W\Upsilon^{\frac{1}{\alpha_2}}\tau^{\frac{\alpha_1}{\alpha_2}}\mathcal{G}_{\alpha_2}((\frac{\tau^{\alpha_2-\alpha_1}}{\Upsilon})^{\frac{1}{\alpha_2}})]$ represents the channel-induced OP influenced by the other vehicles v_i, and the last term $e^{-2\lambda W\tau}$ is associated with the p.d.f. of the variable $\tau = d_1$. This completes the proof of *Corollary 1*.

APPENDIX C
PROOF OF COROLLARY 2

By substituting $\alpha_1 = \alpha_2 = \alpha$ in (13), we have

$$
\begin{aligned}
p_0^{\mathrm{hwy}_2} &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha}\right) \cdot \\
&\quad \times \exp\left[-2\lambda W \Upsilon^{\frac{1}{\alpha}} \mathcal{G}_{\alpha}\left(\Upsilon^{-\frac{1}{\alpha}}\right)\tau\right] \cdot e^{-2\lambda W \tau} \mathrm{d}\tau \\
&= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha}\right) \\
&\quad \times \exp\Big(-2\lambda W \Phi_{\alpha}(\Upsilon)\tau\Big) \cdot e^{-2\lambda W \tau} \mathrm{d}\tau \\
&= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \\
&\quad \times \left[-\frac{\sigma^2 \Upsilon}{\mu}\tau^{\alpha} - 2\lambda W\Big(1 + \Phi_{\alpha}(\Upsilon)\Big)\tau\right] \mathrm{d}\tau
\end{aligned} \tag{42}
$$

where the second step is valid according to (12)

$$
\Phi_{\alpha}(\Upsilon) = \Upsilon^{1/\alpha} \int_{\Upsilon^{-1/\alpha}}^{+\infty} \frac{1}{1+u^{\alpha}} \mathrm{d}u = \Upsilon^{1/\alpha} \mathcal{G}_{\alpha}\left(\Upsilon^{-1/\alpha}\right). \tag{43}
$$

This completes the proof of (15) in *Corollary 2*.

Following (42), we can further consider the specific scenario of having a path loss of $\alpha = 2$, which is common in the highway vehicular network scenario of [30]. By substituting $\alpha = 2$ in (42), we have

$$
\begin{aligned}
p_0^{\mathrm{hwy}_2} &= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp\left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{2}\right) \\
&\quad \times \exp\left(-2\lambda W \Upsilon^{\frac{1}{2}} \mathcal{G}_{2}\left(\Upsilon^{-\frac{1}{2}}\right)\tau\right) \cdot e^{-2\lambda W \tau} \mathrm{d}\tau \\
&= 1 - 2\lambda W \int_{\tau=0}^{+\infty} \exp \\
&\quad \times \left(-\frac{\sigma^2 \Upsilon}{\mu}\tau^{2} - 2\lambda W\left(1 + \sqrt{\Upsilon}\arctan\sqrt{\Upsilon}\right)\tau\right) \mathrm{d}\tau \\
&= 1 - 2\lambda W \sqrt{\frac{\pi}{\chi_1(\Upsilon)}} \exp\left(\frac{\chi_2^2(\Upsilon)}{4\chi_1(\Upsilon)}\right) \\
&\quad \times Q\left(\frac{\chi_2(\Upsilon)}{\sqrt{2\chi_1(\Upsilon)}}\right)
\end{aligned} \tag{44}
$$

where the second step is valid because $\arctan(1/u) = \int_u^{+\infty} \frac{1}{1+u^2} \mathrm{d}u$ and the last step exploits the following exponential integration properties [46]:

$$
\int_{\tau=0}^{+\infty} \exp(-a\tau^2 - b\tau)\mathrm{d}\tau = \sqrt{\frac{\pi}{a}} \exp\left(\frac{b^2}{4a}\right) Q\left(\frac{b}{\sqrt{2a}}\right) \tag{45}
$$

with the Q-function given by $Q(x) = \frac{1}{2\pi}\int_x^{+\infty} \exp(-y^2/2)\mathrm{d}y$. This completes the proof of *Corollary 2*.

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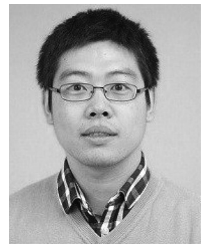

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