Resource Allocation for D2D-Enabled Vehicular Communications
Le Liang, Student Member, IEEE, Geoffrey Ye Li, Fellow, IEEE, and Wei Xu, Senior Member, IEEE

Abstract—The widely deployed cellular network, assisted with device-to-device (D2D) communications, can provide a promising solution to support efficient and reliable vehicular communications. Fast channel variations caused by high mobility in a vehicular environment need to be properly accounted for when designing resource allocation schemes for the D2D-enabled vehicular networks. In this paper, we perform spectrum sharing and power allocation based on only on slowly varying large-scale fading information of wireless channels. Pursuant to differing requirements for different types of links, i.e., high capacity for vehicle-to-infrastructure (V2I) links and ultrareliability for vehicle-to-vehicle (V2V) links, we attempt to maximize the ergodic capacity of the V2I connections while ensuring reliability guarantee for each V2V link. Sum ergodic capacity of all V2I links is first taken as the optimization objective to maximize the overall V2I link throughput. Minimum ergodic capacity maximization is then considered to provide a more uniform capacity performance across all V2I links. Novel algorithms that yield optimal resource allocation and are robust to channel variations are proposed. Their desirable performance is confirmed by computer simulation.

Index Terms—Device-to-device (D2D) communications, vehicular communications, spectrum sharing, power allocation.

I. INTRODUCTION

VEHICULAR communications have gained attention recently due to its potential to improve road safety and traffic efficiency, as well as provide richer infotainment (information and entertainment) experience on wheels [1]–[4]. The 3rd Generation Partnership Project (3GPP) and the European Union Mobile and wireless communications Enablers for Twenty-twenty (2020) Information Society (METIS) project, among other consortia and standardization bodies, are both coordinating efforts of various parties to enable highly efficient and reliable vehicular communications in future generation wireless networks [5], [6]. As illustrated in Fig. 1, infotainment applications and traffic efficiency messages generally require frequent access to the Internet or remote servers for media streaming, content sharing, etc., involving considerable amount of data exchange, and hence are ideally supported by the high-capacity vehicle-to-infrastructure (V2I) links. Meanwhile, safety-critical information, such as cooperative awareness messages (CAMs) and decentralized environmental notification messages (DENM) [1], usually entails spreading safety related messages among surrounding vehicles either in a periodic or event triggered way. Hence, it is naturally supported by the vehicle-to-vehicle (V2V) links, which impose strict reliability and timeliness requirements. For example, the METIS project requires less than 5 ms of end-to-end latency and transmission reliability of 99.999% for message sizes of about 1600 bytes in such links [6].

IEEE 802.11p, also known as wireless access for vehicular environments (WAVE), is the de facto standard for vehicular communications based on ad hoc networks [2], [7]. However, recent studies [1], [8], [9] show that it suffers from several challenges, such as scalability issues, potentially unbounded channel access delay, lack of quality-of-service (QoS) guarantees, etc., due to its physical and medium access control (MAC) layer design, which was originally optimized for wireless local area networks (WLAN) with low mobility. Moreover, due to its limited radio range and lack of pervasive road side infrastructure, IEEE 802.11p networks can only provide intermittent and short-lived V2I connections. In contrast, cellular networks provide wide coverage and exercise flexible centralized control over network resources, which guarantees optimal performance of the networks. Better still, proximity-based device-to-device (D2D) links, complementing the centralized cellular architecture, will provide direct local...
message dissemination with substantially reduced latency and power consumption, thus suitable for delay-sensitive V2V communications [8]. As a result, the D2D-enabled cellular networks represent a promising solution to enable highly efficient and reliable vehicular communications.

A. Related Work

The D2D communications have been the subject of much recent research endeavor [10], [11]. D2D users can work in two different modes: the reuse mode and the dedicated mode, where D2D users share the same resources as the cellular users and occupy dedicated resources, respectively. The dedicated mode is easier to implement since it causes no interference to the existing cellular users while the reuse mode can further improve the spectral efficiency. Effective radio resource management (RRM) strategies need to be in place to properly coordinate mutual interference between cellular and D2D users in the reuse mode. In [12], the transmit power of D2D users has been restricted such that interference inflicting cellular receivers is controlled when the D2D transmitter reuses cellular resources. An interference limited area control scheme has been proposed in [13] to protect D2D receivers from cellular interference, where D2D users are not allowed to share spectrum with a cellular user located in the interference limited area where the interference-to-noise ratio at the D2D receiver is above a predetermined threshold. In [14], interference nulling has been introduced to control interference from the cellular link to D2D communications when multiple antennas are installed at the base station (BS). The sum rate of both cellular and D2D users has been maximized with a minimum rate guarantee for the cellular user in [15] for a network comprising only a single D2D pair and a single cellular user. For more practical scenarios with multiple cellular and D2D users, spectrum and power allocation design has been considered in [16] and [17]. In [16], the D2D transmit power has been regulated by the BS such that the signal-to-interference-plus-noise ratio (SINR) of D2D links is maximized while the interference experienced by the cellular link is kept at an acceptable level. Moreover, a three-step approach has been proposed in [17] to design power control and spectrum allocation to maximize system throughput with minimum SINR guarantee for both cellular and D2D links.

Conceivably, high mobility in a vehicular environment causes wireless channels to change rapidly over time [18], [19]. Therefore, traditional methods of RRM for D2D communications under full channel state information (CSI) assumption are no longer applicable since it would be hard to track channel variations on such a short time scale. Applying the D2D technique to support vehicular communications thus calls for further investigation into novel RRM strategies to account for fast vehicular channel variations. Along this line, a heuristic location dependent uplink resource allocation scheme has been proposed in [20] for D2D terminals, which features spatial resource reuse with no requirement on full CSI, thus reducing signaling overheads. A framework comprising vehicle grouping, reuse channel selection, and power control has been developed in [21] to maximize the sum rate or minimally achievable rate of D2D users while restraining the aggregate interference to cellular networks. In [9], latency and reliability requirements of vehicular communications have been transformed into optimization constraints computable only using large-scale fading information, and a heuristic algorithm has been developed to address the RRM optimization problem. In [22], multiple resource blocks are allowed to be shared not only between cellular and D2D users but also among different D2D-capable vehicles.

B. Motivation and Contribution

As pointed out above, the majority of existing literature on RRM for traditional D2D communication systems assumes full CSI at the BS, which is unrealistic in vehicular environments due to rapid channel variations caused by mobility. For the few exceptions in, e.g., [9], [20]–[22], where only slow fading information is needed, the system capacity computation does not take into account fast fading effects and thus will not reflect real capacity performance of the network. As a result, the developed resource allocation schemes are generally suboptimal.

In this paper, we propose to support both types of vehicular connections, i.e., V2I and V2V links, under the D2D-enabled cellular architecture where the V2I connectivity is enabled by macro cellular link and the V2V connectivity is supported through localized D2D link to achieve the dual benefits of D2D-enabled cellular networks. We base resource management on slow fading parameters and statistical information of the channel instead of instantaneous CSI to address the challenges caused by the inability to track fast changing wireless channels. Moreover, we identify and incorporate into problem formulation differentiated QoS requirements for V2I and V2V links in correspondence with their supported applications. That is, high link capacity is desired for V2I connections while safety-critical information of V2V connections places greater emphasis on link reliability. Sum and minimum ergodic capacities (long-term average over fast fading) of V2I links are maximized with a minimum QoS guarantee for V2I and V2V links, where the V2V link reliability is ensured by maintaining the outage probability of received SINR below a small threshold. To the best of our knowledge, this is the first work that jointly considers the heterogeneous performance of V2I and V2V links and exploits only the large-scale fading information of the channels for resource allocation while taking a rigorous treatment of small-scale fading effects.

The rest of the paper is organized as follows. The system model is introduced in Section II. Section III considers the sum V2I capacity maximization design with minimum QoS guarantee for V2I and V2V connections, whereas Section IV addresses the resource allocation problem to maximize the minimum V2I capacity. Computer simulation results are presented in Section V and concluding remarks are finally made in Section VI.

II. SYSTEM MODEL

Consider a D2D-enabled vehicular communications network shown in Fig. 1, where there exist $M$ vehicles requiring high-capacity V2I communications, denoted as CUEs (cellular users), and $K$ pairs of vehicles doing local V2V data exchange.
in the form of D2D communications, denoted as DUEs (D2D users). We note that all vehicles are capable of doing both V2I and V2V connections simultaneously, implying that CUEs and DUEs might refer to the same vehicle equipped with multiple radios in this article. We assume that all communicating parties in this paper are equipped with a single antenna. Denote the CUE set as $\mathcal{M} = \{1, \ldots, M\}$ and the DUE set as $\mathcal{K} = \{1, \ldots, K\}$. To improve spectrum utilization efficiency, orthogonally allocated uplink spectrum of CUEs is reused by the DUEs since uplink resources are less intensively used and interference at the BS is more manageable.

The channel power gain, $h_{m,B}$, between CUE $m$ and the BS is assumed to follow

$$h_{m,B} = g_{m,B} \beta_{m,B} A L_{m,B}^\gamma \Delta g_{m,B},$$ (1)

where $g_{m,B}$ is the small-scale fast fading power component and assumed to be exponentially distributed with unit mean, $A$ is the pathloss constant, $L_{m,B}$ is the distance between the $m$th CUE and the BS, $\gamma$ is the decay exponent, and $\beta_{m,B}$ is a log-normal shadow fading random variable with a standard deviation $\zeta$. Channel $h_k$ between the $k$th D2D pair, interfering channel $h_{k,B}$ from the $k$th DUE to the BS, and interfering channel $h_{m,k}$ from the $m$th CUE to the $k$th DUE are similarly defined.

We assume that the large-scale fading components of the channel, i.e., the path loss and shadowing of all links, are known at the BS since they are usually dependent on locations of users and vary on a slow scale [9]. Such information can be estimated at the BS for links between CUEs/DUEs and BS, i.e., $a_{m,B}$ and $a_{k,B}$, while for links between vehicles, i.e., $a_k$ and $a_{m,k}$, the parameters will be measured at the DUE receiver and reported to the BS periodically. Meanwhile, each realization of the fast fading is unavailable at the BS since it varies rapidly in a vehicular environment with high mobility, whereas its statistical characterization is assumed to be known.

To this point, the received SINRs at the BS for the $m$th CUE and at the $k$th DUE can be expressed as

$$\gamma_m^c = \frac{P_m^c h_{m,B}}{\sigma^2 + \sum_{k \in \mathcal{K}} \rho_{m,k} p_k^d h_{k,B}},$$ (2)

and

$$\gamma_k^d = \frac{p_k^d h_k}{\sigma^2 + \sum_{m \in \mathcal{M}} \rho_{m,k} P_m^c h_{m,k}},$$ (3)

respectively, where $P_m^c$ and $p_k^d$ denote transmit powers of the $m$th CUE and the $k$th DUE, respectively, $\sigma^2$ is the noise power, and $\rho_{m,k}$ is the spectrum allocation indicator with $\rho_{m,k} = 1$ indicating that the $k$th DUE reuses the spectrum of the $m$th CUE and $\rho_{m,k} = 0$ otherwise. The ergodic capacity of the $m$th CUE with the assumption of Gaussian inputs is then given by

$$C_m = E[\log_2 (1 + \gamma_m^c)],$$ (4)

where the expectation $E[\cdot]$ is taken over the fast fading distribution.

### III. Sum CUE Capacity Maximization Design

In this section, we develop a robust spectrum and power allocation scheme to improve the vehicular communications performance while taking into account the unique characteristics of D2D-enabled vehicular networks. The proposed scheme depends solely on the slowly varying large-scale channel parameters and only needs to be updated every few hundred milliseconds, thus significantly reducing the signaling overheads than if directly applying traditional resource allocation schemes in vehicular networks.

Recognizing QoS differentiation for different types of links, i.e., large capacity for V2I connections and high reliability for V2V connections, we maximize the sum ergodic capacity of $M$ CUEs while guaranteeing the minimum reliability for each DUE. In addition, we set a minimum capacity requirement for each CUE as well to provide a minimum guaranteed QoS for them. The reliability of DUEs is guaranteed through controlling the probability of outage events, where its received SINR $\gamma_k^d$ is below a predetermined threshold $\gamma_0^d$. The ergodic capacity of CUEs is computed through the long-term average over the fast fading, which implies the codeword length spans several coherence periods over the time scale of slow fading [23]. It should be noted that how close the system performance can approach the ergodic capacity ultimately depends on the temporal variation of the vehicular channels as well as the tolerable delay. Faster variation induces more channel states within a given period, which makes the system performance approach the computed ergodic capacity quicker as the codeword needs to traverse most, if not all, channel states to average out the fading effects. To this end, the radio resource allocation problem in vehicular networks is formulated as

$$\max_{\{P_m^c\},\{p_k^d\}} \sum_{m \in \mathcal{M}} E[\log_2 (1 + \gamma_m^c)]$$ (5)

s. t. $E[\log_2 (1 + \gamma_m^c)] \geq r_0$, $\forall m \in \mathcal{M}$ (5a)

$$P_m^c \leq P_m^c \max, \forall m \in \mathcal{M}$$ (5b)

$$P_k^d \leq P_k^d \max, \forall k \in \mathcal{K}$$ (5c)

$$\sum_{m \in \mathcal{M}} \rho_{m,k} \leq 1, \rho_{m,k} \in \{0, 1\}, \forall k \in \mathcal{K}$$ (5d)

$$\sum_{k \in \mathcal{K}} \rho_{m,k} \leq 1, \rho_{m,k} \in \{0, 1\}, \forall m \in \mathcal{M},$$ (5f)

where $r_0$ is the minimum capacity requirement of the data rate intensive CUEs and $\gamma_0^d$ is the minimum SINR needed by the DUEs to establish a reliable link. $Pr[\cdot]$ evaluates the probability of the input and $p_0$ is the tolerable outage probability at the physical layer of the V2V links. $P_m^c \max$ and $p_k^d \max$ are the maximum transmit powers of the CUE and DUE, respectively. Constraints (5a) and (5b) represent the minimum capacity and reliability requirements for each CUE and DUE, respectively. (5c) and (5d) ensure that the transmit powers of CUEs and DUEs cannot go beyond their maximum limit. (5e) and (5f) mathematically model our assumption that the spectrum of one CUE can only be shared with a
single DUE and one DUE is only allowed to access the spectrum of a single CUE. This assumption reduces the complexity brought by the complicated interference scenarios in D2D-enabled vehicular networks and serves as a good starting point to study the challenging resource allocation problem in vehicular networks.

The proposed optimization problem represents a novel formulation that factors in the unique features of time varying channels of vehicular communications as well as differentiated QoS requirements for V2I and V2V links. However, this is a highly nonconvex optimization problem due to its combinatorial nature and the complicated objective function. We attempt to approach the optimization problem in (5a) in two steps inspired by [17]. First, we exploit the separability of power allocation and spectrum reuse pattern design by noting that interference exists only within each CUE-DUE reuse pair, e.g., the $k$th DUE sharing the band of the $m$th CUE, the power allocation problem for the single CUE-DUE pair is simplified into

$$\max_{P_m, P_d} \mathbb{E} \left[ \log_2 (1 + \gamma_m) \right]$$

s.t. $Pr(\gamma_k^d \leq \gamma_k^c) \leq p_0$

$$0 \leq P_m \leq P_{c, max}$$

$$0 \leq P_k^d \leq P_{d, max}^c$$

where the minimum capacity constraint for the CUE is temporarily left out and would be accounted for in the next step.

We evaluate the reliability constraint for the $k$th DUE in the following lemma, proved in Appendix A, and then visually depict the feasible regions of the simplified single pair power optimization problem described above.

**Lemma 1:** The reliability constraint for the $k$th DUE, i.e., (6a) in the proposed single pair power allocation problem in (6a), can be expressed as

$$P_m^c \leq \frac{\alpha_k P_k^d}{\gamma_0} \left( e^{\frac{-\gamma_0^d P_k^d}{P_k^m \alpha_k}} - 1 \right) \triangleq f \left( P_k^d \right).$$

Considering $P_m^c \geq 0$ and from (7), we obtain the zero-crossing point by setting $f \left( P_k^d \right) = 0$ as

$$P_k^d = \frac{-\gamma_0^d \sigma^2}{\alpha_k \ln(1 - p_0)} \Delta \frac{P_k^d}{P_{k, min}}.$$  

It can be observed from (7) that $f \left( P_k^d \right)$ is monotonically increasing with respect to the DUE power, $P_k^d$, in the range of $(0, +\infty)$. This observation makes intuitive sense as an increase of the DUE power would lead to a higher interference margin, implying the DUE is more tolerable to interference from the CUE.

With the closed-form expression for reliability constraint (6a) given in Lemma 1, the feasible regions of (6a) are plotted in Fig. 2, where $P_{c, max}^d = f \left( P_{c, max}^d \right)$ and $P_k^d = f^{-1} \left( P_k^c \right)$. Note that $P_{c, max}^d$ can be obtained through bisection search over the function $f(\cdot)$, which is a monotonically increasing function in the range of interest. As shown in the figure, the feasible regions are classified into two cases depending on the magnitudes of $P_{c, max}^d$ and $P_{c, max}^d$. We now derive the optimal solution to (6a) in the following theorem, proved in Appendix B.

1The other zero-crossing point $P_k^d = 0$ is irrelevant here.
Theorem 1: The optimal power allocation solution to optimization problem (6a) is given by

\[ P^c_m = \min(P^c_{\text{max}}, P^d_{\text{max}}), \]

and

\[ P^d_k = \min(P^d_{\text{max}}, P^d_{c,\text{max}}). \]

Theorem 1 yields the optimal power allocation for a single CUE-DUE pair that maximizes ergodic capacity of the investigated CUE and ensures reliability for its reusing DUE. As mentioned earlier, interference exists only within each reuse pair and the original resource allocation problem in (5a) to maximize the sum ergodic capacity of all CUEs has been decoupled into two major parts. The first part deals with the optimal power allocation for each single pair, which has been given by Theorem 1. The rest is to perform optimal spectrum reuse pair matching to maximize the sum ergodic capacity of CUEs while respecting all QoS constraints.

B. Pair Matching for All Vehicles

To this end, we have obtained the optimal power allocation for each CUE-DUE pair. In the next step, we need to eliminate those CUE-DUE combinations that do not satisfy the minimum QoS requirement for the CUE, i.e., (5aa), even when the optimal allocation scheme obtained from (9) is applied. The closed-form expression for the ergodic capacity of the \( m \)-th CUE when sharing spectrum with the \( k \)-th DUE, defined as

\[ C_{m,k}(P^c_m, P^d_k) = \log_2(1 + \gamma^c_m), \]

is derived in the following lemma, proved in Appendix C.

Lemma 2: The ergodic capacity, \( C_{m,k}(P^c_m, P^d_k) \), of the \( m \)-th CUE when sharing spectrum with the \( k \)-th DUE is given by

\[ C_{m,k}(P^c_m, P^d_k) = \frac{a}{(a-b) \ln 2} \left[ e^{\frac{1}{a}} E_1\left(\frac{1}{a}\right) - e^{\frac{1}{b}} E_1\left(\frac{1}{b}\right) \right], \]

where \( a = \frac{P^c_m}{P^d_k}, \quad b = \frac{P^d_k}{P^c_m}, \quad \) and \( E_1(x) = \int_x^{\infty} e^{-t} t dt \) is the exponential integral function of the first order [25].

Substituting the optimal power allocation (9) in (10) yields the maximum ergodic capacity achieved when the \( m \)-th CUE shares its spectrum with the \( k \)-th DUE, denoted as \( C^*_{m,k} \). If it is less than \( r^c_0 \), then this combination cannot meet the minimum capacity requirement for the CUE. Therefore, such a CUE-DUE pair is not feasible and we set \( C^*_{m,k} = -\infty \), i.e.,

\[ C^*_{m,k} = \begin{cases} C_{m,k}(P^c_m, P^d_k), & \text{if } C_{m,k}(P^c_m, P^d_k) \geq r^c_0, \\ -\infty, & \text{otherwise}. \end{cases} \]

After evaluating all possible combinations of the CUE-DUE pairs, the resource allocation problem (5a) reduces to

\[ \max_{\{\rho_m,k\}} \sum_{m \in M} \sum_{k \in K} \rho_{m,k} C_{m,k} \]

s.t. \[ \sum_{m \in M} \rho_{m,k} \leq 1, \quad \rho_{m,k} \in \{0,1\}, \quad \forall k \in K \]

\[ \sum_{k \in K} \rho_{m,k} \leq 1, \quad \rho_{m,k} \in \{0,1\}, \quad \forall m \in M. \]

which turns out to be a maximum weight bipartite matching problem and can be efficiently solved by the Hungarian method in polynomial time [24].

From the above discussion, our algorithm to find the optimal solution to the resource allocation problem in (5a) for D2D-enabled vehicular communications can be summarized in Table I.2 Supposing an accuracy of \( \epsilon \) is required, the bisection search for the optimal power allocation of a single CUE-DUE pair as given in (9) requires \( \log(1/\epsilon) \) iterations. This leads to the total complexity of \( O(KM \log(1/\epsilon)) \) to compute the optimal power allocation for all CUE-DUE pairs. The Hungarian method will solve the pair matching problem in \( O(M^3) \) time assuming \( M \geq K \). Therefore, the total complexity of the proposed algorithm is \( O(KM \log(1/\epsilon) + M^3) \).

IV. MINIMUM CUE CAPACITY MAXIMIZATION DESIGN

The sum capacity maximization design considered in Section III can ensure a high overall throughput from the network operator’s perspective. However, it tends to be unfair from each CUE’s point of view, especially for those vehicles experiencing bad channel conditions. In such a case, the CUEs with bad channel conditions will be sacrificed in exchange for the overall performance improvement. In this section, we will address this issue by maximizing the minimum capacity among all CUEs so as to provide a more uniform performance across all CUEs.

The proposed optimization problem is stated as

\[ \max_{\{\rho_{m,k}\}} \min_{m \in M} \mathbb{E}[\log_2(1 + \gamma^c_m)] \]

s.t. \( (5a) - (5f) \).
From [26] and [27], this max-min optimization problem is guaranteed to reach the Pareto boundary where none of the CUEs’ ergodic capacity can be improved without degrading other CUEs’ ergodic capacity. This is a key concept in multi-objective optimization (MOO) and the max-min formulation in (13) is in fact a special case of the weighted Chebyshev objective function with all weights set to one, which is the safest choice in converting MOO to single objective optimization (SOO) while ensuring Pareto optimality [26]. As such, the solution to the proposed problem can be guaranteed to be Pareto optimal.

A. Resource Allocation Design

To solve the proposed resource allocation problem in (13), we make use of the optimal power control results given in (9) for each CUE-DUE pair and the closed-form ergodic capacity for each CUE derived in (10), by acknowledging that interference only occurs within each CUE-DUE pair. Then the capacity for each CUE derived in (10), by acknowledging that interference only occurs within each CUE-DUE pair. Then the original problem in (13) is simplified into the following form

\[
\max_{(\rho_{m,k})} \min_{m \in M} \sum_{k \in \mathcal{K}} \rho_{m,k} C^*_{m,k} \quad (14)
\]

s.t. \[
\sum_{m \in M} \rho_{m,k} \leq 1, \quad \rho_{m,k} \in [0, 1], \quad \forall k \in \mathcal{K} \quad (14a)
\]

\[
\sum_{k \in \mathcal{K}} \rho_{m,k} \leq 1, \quad \rho_{m,k} \in [0, 1], \quad \forall m \in M. \quad (14b)
\]

We further attempt to develop a low-complexity algorithm to solve the optimization problem in (14a) through exploiting the Hungarian method, which has polynomial time computational complexity. The proposed optimal resource allocation algorithm is listed in Table II and comprises two essential parts.

The first part checks in polynomial time whether an arbitrarily given number \(\tau\) is above the desired optimal minimum ergodic capacity or not. It operates as follows.

1. Initialize an all-zero matrix \(F\) of size \(M \times K\).
2. Scan each element of the capacity matrix, \(\{C^*_{m,k}\}\), obtained from Algorithm 1 and if it is less than \(\tau\), the corresponding entry of \(F\) to 1 and leave it as 0 otherwise, i.e., \(\forall m, k\),

\[
F_{m,k} = \begin{cases} 
1, & \text{if } C^*_{m,k} < \tau, \\
0, & \text{otherwise.}
\end{cases} \quad (15)
\]

3. Apply the Hungarian method to \(F\) and return the lowest total cost, denoted as \(c\), i.e., the sum of all the assigned elements. If \(c\) equals zero, all elements of such an assignment are no smaller than \(\tau\), or equivalently, \(\tau\) is less than or equal to the desired optimal minimum ergodic capacity. Correspondingly, if \(c\) is greater than 0, then there exists no assignment that guarantees that all the assigned elements are no smaller than \(\tau\), i.e., \(\tau\) is greater than the desired optimal minimum ergodic capacity.

The second part starts with ordering all \(KM\) elements of the original capacity matrix, \(\{C_{m,k}\}\), and then searches for the position of the optimal minimum ergodic capacity using bisection search based on the checking method derived in the first part. Finally, the spectrum sharing assignment is what the Hungarian method yields when the bisection search ends.

The major computational burden of the proposed algorithm lies in the generation of the capacity matrix, \(\{C_{m,k}\}\), whose complexity is \(O(KM \log(1/\epsilon))\), the ordering of all elements in \(\{C_{m,k}\}\) whose complexity is \(O(KM \log(KM))\), and the bisection search for the optimal value based on the Hungarian method with complexity \(O(M^3 \log M)\) if \(M \geq K\). Then the total computational complexity of Algorithm 2 amounts to \(O(KM \log(1/\epsilon) + KM \log(KM) + M^3 \log M)\).

V. Simulation Results

In this section, simulation results are presented to validate the proposed spectrum and power allocation algorithms for D2D-enabled vehicular networks. We follow the simulation setup for the freeway case detailed in 3GPP TR 36.885 [5] and model a multi-lane freeway that passes through a single cell where the BS is located at its center as illustrated in Fig. 1. The vehicles are dropped on the roads according to spatial Poisson process and the vehicle density is determined by the vehicle speed. The \(M\) CUEs and \(K\) DUEs are randomly chosen among generated vehicles, where DUE pairs are always formed between neighboring vehicles and the CUEs are assumed to have equal shares of the total bandwidth. The major simulation
parameters are listed in Table III and the channel models for V2I and V2V links are described in Table IV. Note that all parameters are set to the values specified in Tables III and IV by default, whereas the settings in each figure take precedence wherever applicable. The results in each figure are obtained from averaging a minimum of 10,000 channel realizations and in particular, Fig. 4 is plotted with 1,000,000 channel realizations.

Figs. 3 demonstrates the sum and minimum ergodic capacities of CUEs achieved by our proposed algorithms with varying DUE outage probability $p_0$, assuming $P_{d\max} = P_{c\max} = 23$ dBm. It is observed that both sum and minimum ergodic capacities of CUEs achieved by both Algorithms 1 and 2 get larger if higher outage probability of DUEs is allowed. This is due to the fact that higher acceptable outage of DUEs renders them more tolerable to interference from CUEs, thus encouraging CUEs to increase their transmit powers. As a result, the CUE capacity grows larger. From Fig. 3(a), the performance of Algorithm 1 is well close to the ideal benchmark scheme in terms of sum capacity at fairly low outage probability, e.g., $p_0 = 0.1$. As for the minimum CUE capacity shown in Fig. 3(b), Algorithm 2 shows superior performance even over the ideal benchmark when the acceptable outage is a bit larger than 0.001. These are encouraging findings as the proposed resource allocation schemes make use of slowly varying large-scale fading parameters only and update every few hundred milliseconds. Nonetheless, they can achieve performance measurably close to the genie-aided benchmark scheme (or even surpass it if minimum capacity maximization is pursued), which requires accurate real-time CSI of all links and is inapplicable in a vehicular environment featuring high mobility.

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**TABLE III**

<table>
<thead>
<tr>
<th>Parameter</th>
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<td>Carrier frequency</td>
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<td>Bandwidth</td>
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<td>Cell radius</td>
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<td>BS antenna height</td>
<td>25 m</td>
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<td>BS antenna gain</td>
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<td>BS receiver noise figure</td>
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<td>Distance between BS and highway</td>
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<td>Vehicle receiver noise figure</td>
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<td>Vehicle drop model</td>
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</tr>
<tr>
<td>Number of lanes</td>
<td>3 in each direction (6 in total)</td>
</tr>
<tr>
<td>Lane width</td>
<td>4 m</td>
</tr>
<tr>
<td>Vehicle density</td>
<td>Average inter-vehicle distance is 2.5 sec × absolute vehicle speed.</td>
</tr>
<tr>
<td>Minimum capacity of DUE $r_0^C$</td>
<td>0.5 bps/Hz</td>
</tr>
<tr>
<td>SINR threshold for DUE $\gamma_0^C$</td>
<td>5 dB</td>
</tr>
<tr>
<td>Reliability for DUE $p_0$</td>
<td>0.001</td>
</tr>
<tr>
<td>Number of DUEs $K$</td>
<td>20</td>
</tr>
<tr>
<td>Number of CUEs $M$</td>
<td>20</td>
</tr>
<tr>
<td>Maximum CUE transmit power $P_{\text{max}}^C$</td>
<td>17, 23 dBm</td>
</tr>
<tr>
<td>Maximum DUE transmit power $P_{\text{max}}^D$</td>
<td>17, 23 dBm</td>
</tr>
<tr>
<td>Noise power $\sigma^2$</td>
<td>-114 dBm</td>
</tr>
<tr>
<td>Bisection search accuracy $\epsilon$</td>
<td>$10^{-6}$</td>
</tr>
</tbody>
</table>

**TABLE IV**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>V2I Link</th>
<th>V2V Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pathloss model</td>
<td>$128.1 + 37.6\log_{10} d$, $d$ in km</td>
<td>LOS in WINNER + B1 [29]</td>
</tr>
<tr>
<td>Shadowing distribution</td>
<td>Log-normal</td>
<td>Log-normal</td>
</tr>
<tr>
<td>Shadowing standard deviation $\xi$</td>
<td>8 dB</td>
<td>3 dB</td>
</tr>
<tr>
<td>Fast fading</td>
<td>Rayleigh fading</td>
<td>Rayleigh fading</td>
</tr>
</tbody>
</table>

---

Fig. 3. Capacity performance of CUEs with varying DUE outage probability $p_0$, assuming $P_{d\max} = P_{c\max} = 23$ dBm.
To demonstrate the superiority of our proposed scheme when only large-scale fading information is available at the BS, we compare in Fig. 4(a) the cumulative distribution functions (CDF) of the instantaneous sum CUE capacity achieved by Algorithms 1 and 2 against the SOLEN scheme developed in [9]. To achieve fair comparison, we exploit the method given in [9, Lemma 1] to generate an equivalent SINR threshold expressed in terms of large-scale fading parameters only. In addition, the minimum capacity requirement in the original problem formulation is not considered as there is no convenient way to convert such a constraint into an equivalent form to be used for the SOLEN scheme. We observe that the proposed Algorithm 1 achieves strictly better performance than the SOLEN scheme of [9] while Algorithm 2 has the worst performance when the maximum sum CUE capacity is the system metric. This validates the superior performance of the proposed Algorithm 1 in such cases. The reason for the performance gain of Algorithm 1 is twofold. The first is that Algorithm 1 takes a rigorous treatment of the small-scale fading effect when computing the capacity of V2I links, i.e., calculating the ergodic capacity in contrast to using only large-scale fading parameters to approximate the capacity as in [9]. The second reason is that the approach taken in [9] is not able to achieve exactly the targeted SINR threshold of V2V links, as illustrated in Fig. 4(b), where an arbitrarily chosen DUE’s instantaneous SINR of SOLEN is found to slightly exceed 5 dB (the desired threshold) at the targeted outage probability of 0.01. Meanwhile, our proposed Algorithms 1 and 2 achieve exactly 5 dB at the outage probability of 0.01. This translates to stricter reliability requirements of V2V links in SOLEN, thus reducing the feasible region of power control parameters and degrading the capacity of V2I links. These two aspects also form the major differences between our proposed algorithms and the existing one in [9]. However, we also notice that the performance gain of Algorithm 1 is minimal, which might be due to the insensitivity of capacity to the small-scale fading effect and the fact that the SINR overshooting of SOLEN is essentially small.

Fig. 5 shows the sum and minimum ergodic capacities of all CUEs with an increasing vehicle speed on the road,
respectively. From the figures, both sum and minimum CUE capacities decrease as the vehicles move faster. This is because higher speed induces sparser traffic according to the simulation setup, which would on average increase inter-vehicle distance and give rise to less reliable V2V links with lower received power. As such, less interference from CUEs can be tolerated given the maximum transmit power constraints of DUEs, which leads to less power being allocated to CUEs and decreases both their sum and minimum ergodic capacities. It also reveals that Algorithm 1 achieves higher sum ergodic capacity than Algorithm 2 while the reverse is true when comparing the minimum ergodic capacity. This makes sense since Algorithm 1 aims to maximize the sum ergodic capacity while Algorithm 2 takes the minimum ergodic capacity as its design objective. It is also interesting to note in Fig. 5(a) that an increase of maximum transmit power has a relatively constant impact on the sum CUE capacity performance of both Algorithms 1 and 2 with respect to the vehicle speed increase. However, this does not hold when we investigate the minimum CUE capacity as shown in Fig. 5(b). At a low vehicle speed, a 6 dBm increase of the maximum transmit power brings significant gains for both Algorithms 1 and 2, e.g., some 40% increase at 60 km/h. In contrast, at a very high speed, e.g., 140 km/h, the power increase has limited impact, which is especially true when we focus on Algorithm 1 in Fig. 5(b).

Fig. 6 demonstrates the sum and minimum ergodic capacities of CUEs with respect to increasing SINR threshold for DUEs, respectively. We observe that in both cases, the investigated ergodic capacity will decrease when the minimum QoS requirement for DUEs grows large. Such performance degradation results from the reduced interference tolerability of DUEs due to an increase in their required SINR threshold, which will impose stricter constraints on the allowable transmit power of the pairing CUEs. Reduced transmit power of CUEs directly translates into a decrease of the sum and minimum ergodic capacities they are capable of achieving given all QoS constraints satisfied. It is also observed that a 6 dBm increase of maximum transmit power has roughly uniform impact on the sum CUE capacity with respect to growing $\gamma_d^0$ while for the minimum CUE capacity, the impact gets smaller with increasing $\gamma_d^0$. 

Fig. 6. Capacity performance of CUEs with varying DUE SINR threshold $\gamma_d^0$, assuming $P_{d_{\text{max}}} = P_{c_{\text{max}}}$.

Fig. 7. Capacity performance of CUEs with varying number of DUEs, assuming $P_{d_{\text{max}}} = P_{c_{\text{max}}}$ and $M = 40$. 

(a) Sum ergodic capacity of CUEs.

(b) Minimum ergodic capacity of CUEs.

(b) Minimum ergodic capacity of CUEs.
Fig. 7 shows the impact of the number of active V2V links on the quality of V2I connections. From the figures, as there are more and more V2V links sharing V2I’s spectrum, both the sum and minimum CUE capacities decrease due to the growing amount of interference generated from V2V links. From Fig. 7(a), Algorithm 2 is more sensitive to the change of V2V numbers in terms of sum CUE capacity as evidenced from the steep slope of its sum capacity curve. As for the minimum CUE capacity in Fig. 7(b), Algorithm 1 achieves a 6 dBm increase of maximum transmit power while the impact gets weaker for the minimum CUE capacity with increasing number of active V2V links.

VI. CONCLUSION

In this paper, we have investigated the spectrum sharing and power allocation design for D2D-enabled vehicular networks. Due to fast channel variations arising from high vehicle mobility, instantaneous CSI is hard to track in practice, rendering traditional resource allocation schemes for D2D-based cellular networks requiring full CSI inapplicable. To address this issue, we have taken into account the differentiated QoS requirements of vehicular communications and formulated optimization problems aiming to design a resource allocation scheme based on slowly varying large-scale fading information only. Robust algorithms have been proposed to maximize the sum and minimum ergodic capacity of V2I links, respectively while ensuring reliability for all V2V links.

The current work is limited to allowing spectrum sharing within a single CUE-DUE pair while excluding more general spectrum reuse. Future works include relaxing such constraints and allowing multiple resource blocks to be shared by both V2I and V2V links, i.e., each resource block can be accessed by different V2I or V2V links and each vehicular link can exploit different resource blocks. The problem of optimal resource allocation will be studied accordingly.

APPENDIX A

PROOF OF LEMMA 1

Given an arbitrary reuse pattern, e.g., $\rho_{m,k} = 1$, and substituting the channel model (1) in (6aa), we derive the reliability constraint as

$$
\Pr(\gamma_k^d \leq \gamma_0^d) = \Pr \left( \frac{P_k^d a_k g_k}{\sigma^2 + P_m^d a_m k g_{m,k}} \leq \gamma_0^d \right) = \int_0^{\infty} \int_0^{\gamma_0^d} \left( e^{-g_{m,k}} \right) \frac{g_{m,k} g_{m,k}}{P_k^d a_k g_k} \, dg_{m,k} \leq \gamma_0^d \\
= 1 - \frac{P_k^d a_k}{P_k^d a_k + \gamma_0^d P_m^d a_m k} \leq \rho_0,
$$

where we have assumed that $g_k$ and $g_{m,k}$ are independent and identically distributed (i.i.d.) exponential random variables with unit mean. Rearranging the terms from the last inequality completes the proof.

APPENDIX B

PROOF OF THEOREM 1

Assuming that $g_{m,B}$ and $g_{k,B}$ are i.i.d. exponential random variables with unit mean, the ergodic capacity, $C_{m,k}(P_{m}^c, P_{k}^d)$, of the $m$th CUE in (6a) when sharing the spectrum with the $k$th DUE can be written as

$$
C_{m,k}(P_{m}^c, P_{k}^d) = \mathbb{E} \left[ \log_2 \left( 1 + \frac{P_{m}^c a_m g_{m,B} g_{m,k}}{\sigma^2 + P_{k}^d a_k g_{k,B}} \right) \right] = \int_0^{\infty} \int_0^{\infty} \log_2 \left( 1 + \frac{g_{m,k}}{\sigma^2 + P_{k}^d a_k g_{k,B} g_{m,B}} \right) \times e^{-(g_{m,B}+g_{k,B})} g_{m,B} g_{k,B} \, dg_{m,B} \, dg_{k,B} (17)
$$

from which we can easily make the following observations

- With fixed $P_{k}^d$, the ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ increases monotonically with $P_{m}^c$.
- With fixed $P_{m}^c$, the ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ decreases monotonically with $P_{k}^d$.

These observations lead to the conclusion that the optimal solution of (6a) can only reside at the upper boundary line of the feasible region defined by $P_m^c = f(P_k^d)$ from $P_{k,\min}^d$ up to the point $(P_{k,\max}^d, P_{m,\max}^c)$ for Case I or $(P_{k,\max}^d, P_{m,\max}^c)$ for Case II in Fig. 2, by acknowledging the fact that $P_m^c = f(P_k^d)$ is a monotonically increasing function in the range of $(P_{k,\min}^d, +\infty)$.

What remains is to study the ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ along the upper boundary line which could be done by substituting $P_m^c = f(P_k^d)$ in (17). The SINR term $\gamma_m^c$ is then given by

$$
\gamma_m^c = \frac{P_m^c a_m g_{m,B} g_{m,k}}{\sigma^2 + P_k^d a_k g_{k,B} g_{m,B}}
$$

which can be shown to monotonically increase with $P_k^d$ in the range $(P_{k,\min}^d, +\infty)$. Hence, the optimal power allocation solution to the problem (6a) is the intersection point $(P_{k,\max}^d, P_{m,\max}^c)$ for Case I or $(P_{k,\max}^d, P_{m,\max}^c)$ for Case II, which can be written in a compact form as in (9).

APPENDIX C

DERIVATION OF EROGIC CAPACITY IN LEMMA 2

The ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ can be written as

$$
C_{m,k}(P_{m}^c, P_{k}^d) = \mathbb{E} \left[ \log_2 \left( 1 + \frac{P_{m}^c a_m g_{m,B} g_{m,k}}{\sigma^2 + P_{k}^d a_k g_{k,B}} \right) \right] = \mathbb{E} \left[ \log_2 \left( 1 + \frac{a X}{1 + b Y} \right) \right],
$$

where $X$ and $Y$ are independent exponential random variables with unit mean and

$$
X = \frac{P_{m}^c a_m g_{m,B} g_{m,k}}{\sigma^2 + P_{k}^d a_k g_{k,B}}, \quad Y = \frac{P_{m}^c a_m g_{m,B} g_{m,k}}{\sigma^2 + P_{k}^d a_k g_{k,B}}.
$$

These conclusions lead to the following observations

- With fixed $P_{k}^d$, the ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ increases monotonically with $P_{m}^c$.
- With fixed $P_{m}^c$, the ergodic capacity $C_{m,k}(P_{m}^c, P_{k}^d)$ decreases monotonically with $P_{k}^d$.
where we denote $g_{m,b}$ and $g_{k,b}$ by $X$ and $Y$, respectively, and 
define $a = \frac{P_{c,m}}{\sigma}$ and $b = \frac{P_{d,k}}{\sigma}$. Defining $Z = \frac{aX}{1 + bY}$ and assuming $g_{m,b}$ and $g_{k,b}$ are i.i.d. exponential random variables
with unit mean, we have its CDF as
\[ F_Z(z) = \Pr\left(\frac{aX}{1 + bY} \leq z\right) = \int_0^\infty dy \int_0^{(1+b)y/2a} e^{-(1+y)x} dx = 1 - e^{-\frac{z}{a}} e^{-\frac{z}{a+b}}. \] (20)

Then, we obtain the ergodic capacity of the $m$th CUE as
\[ C_{m,k}(P_{m}^{c}, P_{k}^{d}) = \frac{1}{\ln 2} \int_0^\infty \ln(1+z) f_Z(z) dz = \frac{1}{\ln 2} \int_0^\infty \frac{1}{1 + z} dz - \int_0^\infty \frac{e^{-\frac{z}{a}}}{z + a} dz \]
\[ = \frac{a}{(a-b) \ln 2} \left[ e^{\frac{z}{a}} E_1\left(\frac{1}{a}\right) - e^{\frac{z}{b}} E_1\left(\frac{1}{b}\right) \right], \] (21)

where we obtain (21) by using integration by parts and (22) follows from [25, eq. (3.352.4)].

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REFERENCES


Le Liang (S’12) received the B.E. degree in information engineering from Southeast University, Nanjing, China, in 2012, and the M.A.Sc. degree in electrical engineering from the University of Victoria, Victoria, BC, Canada, in 2015. He is currently pursuing the Ph.D. degree in electrical engineering with the Georgia Institute of Technology, Atlanta, GA, USA. His research interests include vehicular communications, radio resource management, and MIMO systems.

Geoffrey Ye Li (S’93–M’95–SM’97–F’06) received the B.S.E. and M.S.E. degrees from the Department of Wireless Engineering, Nanjing Institute of Technology, Nanjing, China, in 1983 and 1986, respectively, and the Ph.D. degree from the Department of Electrical Engineering, Auburn University, AL, in 1994. He was a Teaching Assistant and then a Lecturer with Southeast University, Nanjing, China, from 1986 to 1991, a Research and Teaching Assistant with Auburn University from 1991 to 1994, and a Post-Doctoral Research Associate with the University of Maryland at College Park, MD, USA, from 1994 to 1996. He was with AT&T Labs-Research, Red Bank, NJ, USA, as a Senior and then a Principal Technical Staff Member from 1996 to 2000. Since 2000, he has been with the School of Electrical and Computer Engineering, Georgia Institute of Technology, as an Associate Professor and then a Full Professor. He has also been holding a Cheung Kong Scholar title with the University of Electronic Science and Technology of China since 2006. His general research interests include statistical signal processing and communications, with emphasis on cross-layer optimization for spectral- and energy-efficient networks, cognitive radios and opportunistic spectrum access, and practical issues in LTE systems. In these areas, he has authored around 200 journal papers in addition to around 40 granted patents and numerous conference papers. His publications have been cited around 28,000 times. He received the 2010 Stephen O. Rice Prize Paper Award, the 2013 WTC Wireless Recognition Award, and the 2017 Award for Advances in Communication from the IEEE Communications Society, the 2013 James Evans Avant Garde Award, and the 2014 Jack Neubauer Memorial Award from the IEEE Vehicular Technology Society. He also received the 2015 Distinguished Faculty Achievement Award from the School of Electrical and Computer Engineering, Georgia Tech. He has been involved in editorial activities for over 20 technical journals for the IEEE, including the founding Editor-in-Chief of the IEEE 5G TECH FOCUS. He has organized and chaired many international conferences, including the Technical Program Vice-Chair of IEEE ICC’03, the Technical Program Co-Chair of the IEEE SPAWC’11, the General Chair of the IEEE GlobisIP’14, and the Technical Program Co-Chair of the IEEE VTC’16. He has contributed to signal processing for wireless communications in 2005 of the IEEE. He has been recognized as the World’s Most Influential Scientific Mind, also known as a Highly-Cited Researcher, by Thomson Reuters.

Wei Xu (S’07–M’09–SM’15) received the B.Sc. degree in electrical engineering and the M.S. and Ph.D. degrees in communication and information engineering from Southeast University, Nanjing, China, in 2003, 2006, and 2009, respectively. From 2009 to 2010, he was a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, University of Victoria, Canada. He is currently a Professor with the National Mobile Communications Research Laboratory, Southeast University. He has authored over 100 refereed journal and conference papers and holds 15 granted patents. He is currently an Editor of the IEEE COMMUNICATIONS LETTERS. His research interests include cooperative communications, information theory and signal processing for wireless communications. He has been involved in technical program committees for many international conferences including the IEEE Globecom, the IEEE ICC, and the IEEE WCNC. He was an Elected Core Team Member of the Jiangsu Innovation Team in 2012. He received the best paper awards of the IEEE MAPE in 2013, the IEEE/CIC ICCC in 2014, the IEEE Globecom in 2014, and the IEEE ICUWB in 2016. He was a co-recipient of the First Prize Award of the Science and Technology Award in Jiangsu Province in 2014.